Transmission of agricultural cost shocks in the French food supply chain

Documents de travail

N° 2026-07 – Juin 2026

Insee
Mesurer pour comprendre

Swann CHELLY

Insee
Mesurer pour comprendre

Institut national de la statistique et des études économiques

2026/07

TRANSMISSION OF AGRICULTURAL COST SHOCKS IN THE FRENCH FOOD SUPPLY CHAIN*

Swann CHELLY†,

16 Juin 2026

Département des Études Économiques – Timbre G201
88, avenue Verdier – CS 70 058 – 92 541 MONTROUGE CEDEX – France
Tél. : 33 (1) 87 69 59 54 – E-mail : d3e-dg@insee.fr – Site Web Insee : http://www.insee.fr

*I am thankful to Rémi Avignon for discussing my paper. I am grateful to Isabelle Méjean, Corentin Trévien, Raphaël Lafrogne-Joussier, Philippe Askenazy, Charles Labroussse, Mathias Andler, Ugo Di Nallo, Pauline Givord and Cédric Audenis for various discussions and great insights regarding this project. I thank all members of the IPP division and ESANE members I have interacted with and who helped me access the data. Finally, I thank Aurelien D'Isanto for great support when using OpenFoodFact's API.
†Insee : Department of Economic Studies. Email: swann.chelly@insee.fr.

Transmission des chocs de coûts agricoles dans les prix de vente des industriels de l'agroalimentaire

Comment les chocs de coûts agricoles se transmettent-ils à travers les chaînes d'approvisionnement alimentaires ? Cette étude examine la transmission des chocs de coûts des intrants agricoles vers les prix de production des transformateurs alimentaires français entre 2015 et 2023. En utilisant un nouveau jeu de données reliant des indices de prix à la production désagrégée aux indices de prix des intrants agricoles, nous constatons qu'environ 67 % des chocs de coûts agricoles sont répercutés à long terme sur les prix départ usine. Pour les ventes domestiques, le taux de répercussion atteint 77 %, et l'hypothèse d'une répercussion complète peut être rejetée au seuil de 95 %. Les ajustements de prix interviennent dans un délai de cinq trimestres lorsque les ventes sont destinées aux distributeurs, et de trois trimestres lorsqu'elles sont destinées à d'autres clients, ce qui reflète des frictions contractuelles et des renégociations de prix. Nous montrons que les chocs de coûts agricoles expliquent plus de 42 % de la récente hausse des prix départ usine de l'industrie alimentaire sur le marché intérieur, soit légèrement moins que la part des intrants agricoles dans les coûts de production (44 % dans notre échantillon). Cette étude contribue à la littérature sur la répercussion des coûts (cost pass-through) en documentant l'ampleur et la dynamique de la transmission des chocs agricoles à travers différentes catégories de produits alimentaires.

Mots-clés : Inflation et prix, économie agricole, chaînes verticales, répercussion des coûts.

Codes JEL : L11, L16, Q11, E31

Transmission of agricultural cost shocks in the French food supply chain

How do agricultural cost shocks propagate through food-supply chains? This study examines the transmission of agricultural input cost shocks into output prices of French food processors from 2015 to 2023. Using a novel dataset linking disaggregated producer price indices to agricultural input price indices, we find that approximately 67% of agricultural cost shocks are passed through to factory-gate prices in the long run. For domestic sales, the pass-through is 77%, and the full pass-through hypothesis can be rejected at the 95% level. Price adjustments occur within five quarters when selling to retailers and within three quarters when selling to other customers, reflecting contractual friction and price renegotiations. We show that agricultural cost shocks account for over 42% of the recent rise in domestic food industry factory-gate prices, slightly less than the share of agricultural inputs in production costs (44% in our sample). This study contributes to the cost pass-through literature by documenting the magnitude and dynamics of agricultural shock transmission across various food product categories.

Keywords: Inflation and prices, Agricultural Economics, Vertical Chains, Pass-through

JEL Code : L11, L16, Q11, E31

1 Introduction

Between January 2021 and January 2023, consumer prices in France rose by 9.6%, an inflationary episode driven first by energy and subsequently amplified by food prices, which increased by 16% over the same period and accounted for roughly 40% of the rise in inflation (Aldama et al., 2025; INSEE, 2023). While the propagation of energy shocks through French industry is by now well documented (Lafrogne-Joussier et al., 2023; Arquié and Thie, 2023), the determinants of food inflation have received far less attention. In particular, little is known about the mechanisms through which *agricultural* cost shocks are transmitted into industrial food prices—despite sustained policy interest in this question, as reflected in the successive Egalim reforms aimed at governing price formation along the food supply chain.

This paper quantifies that transmission and asks how much of the recent food inflation it can account for. Using a novel firm-level panel built from French administrative data, I estimate that food processors pass approximately 67% of agricultural cost shocks through to their factory-gate prices, and that the 2021–2023 rise in agricultural input costs accounts for 42% of the 26% inflation in factory-gate prices observed in my sample.[1] This is plausibly a lower bound: because the estimate is identified from idiosyncratic, cross-firm cost variation while the 2021–2023 surge was largely a *common* shock, and because common shocks pass through more completely than idiosyncratic ones under nominal rigidity (Wang and Werning, 2022), the contribution of agricultural costs to food inflation was likely larger still.

The credibility of these magnitudes rests on two ingredients. The first is measurement. I construct a firm-level panel that links agricultural inputs to industrial food prices—a connection that has long been missing in the French context. From the *Annual Sectoral Survey* (ESA) I recover annual firm-level agricultural expenditure, and from balance-sheet data (FARE) I recover firm-level cost structures, in particular the share of agricultural inputs in total variable costs. Agricultural inputs account for 35% of variable costs on average,[2] with substantial heterogeneity across firms within the same sector. Combining the annual change in agricultural expenditure with this cost share yields a firm-level measure of the change in agricultural input costs.

The second ingredient is identification. Estimating pass-through requires isolating cost-driven price movements from confounders such as shifts in bargaining power or demand. I link each product in the French food Producer Price Index (PPI) to indices tracking the prices of its agricultural inputs, aggregate these to the firm level, and interact them with the firm's agricultural cost share to construct a shift-share cost-shifter instrument. I then regress changes in firm-level output prices on changes in agricultural input costs, instrumenting the latter with this shifter. The instrument exploits variation in farm-gate prices that shifts processors' costs and is plausibly orthogonal to

[1] This figure refers to the estimation sample, whose factory-gate inflation (26%) is slightly below that of the food industry as a whole.

[2] 44% in the estimation sample.

firm-specific determinants of output prices.

A distinctive feature of this design is what it allows the estimated elasticity to capture. Because the regressor is the firm's *realized* agricultural expenditure—already net of any upstream adjustment through oligopsony power, supplier substitution, or contractual arrangements—the coefficient isolates the response of output prices to a change in realized marginal cost. Incomplete pass-through can therefore be attributed to *downstream* markup adjustment rather than to upstream cost absorption, a separation that comovement-based approaches cannot make. This distinction matters quantitatively: Alviarez et al. (2023) show that ignoring two-sided market power can substantially overstate pass-through.

I find a long-run pass-through of approximately 67%, statistically below unity. The estimate is similar across domestic customers, other processors, and retailers, and somewhat lower for foreign customers; restricting attention to domestic sales raises it to 77%, where full pass-through can be rejected at the 5% but not the 1% level. Incomplete pass-through is consistent with the imperfectly competitive environment in which French processors operate, and points to markup compression as a central feature of price formation in this supply chain.

Finally, I study the *timing* of transmission, which speaks directly to the contracting institutions the policy debate is concerned with. Shocks propagate over roughly five quarters when products are sold to retailers but only three when sold to other customers, consistent with longer chains and more constrained bargaining in the former. French processor–retailer contracts are renegotiated annually, with new prices taking effect in March; yet I find that input shocks are transmitted in every month of the year. Transmission is therefore not confined to the annual bargaining window but operates through renegotiation clauses or automatic indexation throughout the year. While a clean causal evaluation of the Egalim reforms would require a credible control group that the data do not afford, this evidence is informative about whether their intended adjustment mechanisms are operative.

Related literature. This study contributes to the extensive empirical literature on pass-through. While a large part of this literature focuses on the transmission of exchange rate shocks (Burstein and Gopinath, 2014; Amiti et al., 2014, 2019), I examine the transmission of commodity cost shocks in the food supply chain, following the earlier work of Peltzman (2000); Nakamura and Zerom (2010); Hong and Li (2017); Sangani (2023). Specifically, I link farmer gate prices to commodity price indices across various markets and analyze the comovement between these prices using an instrumental variable (IV) strategy. The results confirm earlier findings in this sector: changes in the log prices of agricultural inputs are only partially passed through to factory-gate prices. Whereas existing studies typically measure pass-through from the comovement between input and output price indices, my empirical strategy combines an instrumental variable approach with highly disaggregated fixed effects, enabling a more precise identification of the pass-through component driven by the downstream market structure: the markup adjustment channel (Weyl and Fabinger, 2013).

Beyond estimating the magnitude of pass-through, this study also contributes to the literature by incorporating lags into pass-through regressions to examine the timing of shock propagation. Nakamura and Zerom (2010) show that the transmission of coffee commodity costs into wholesale prices takes around six quarters, with half of the adjustment occurring in the first quarter. Lafrogne-Joussier et al. (2023) find that energy cost shocks propagate much faster, mostly within a single quarter. Using a similar approach, I find that agricultural cost shocks are transmitted to factory gate prices within five quarters, with most of the adjustment occurring in the first quarter. Moreover, I document heterogeneity across customers: the propagation takes five quarters when the customer is a retailer, but only three quarters when the customer is another processor.

This study also contributes to the emerging literature on the recent inflationary period. di Giovanni et al. (2022) highlight the role of supply chain bottlenecks during the early phase of inflation (2020–2021), while Aldama et al. (2025) show that, in France, the main drivers of post-pandemic inflation were energy and food shocks. This underscores the importance of understanding the origins of food shocks in France during the pandemic. Lafrogne-Joussier et al. (2023), using the same dataset as in this paper merged with firm-level data on energy usage, find that energy cost shocks are fully transmitted along the supply chain, with stronger pass-through and greater asymmetry, in favor of positive shocks, during the inflation period. Similarly, Arquié and Thie (2023) document excess pass-through of energy shocks at the sectoral level in more concentrated industries. My contribution is to analyze a different type of shock: agricultural commodity cost shocks. Whereas the average energy cost share in the French industry is 2.5% (Lafrogne-Joussier et al., 2023), the average agricultural cost share for French food processors is 35% and 44% for largest firms. Thus, I focus on a shock that affects a substantial share of these firms' variable costs.

The remainder of this paper is organized as follows. Section 2 presents the context of the estimation strategy and the data. Section 3 reports the pass-through estimate, its decomposition across customers, and an estimation of the share of observed inflation that can be attributed to the transmission of agricultural cost shocks. Finally, Section 4 analyzes the timing of shock propagation.

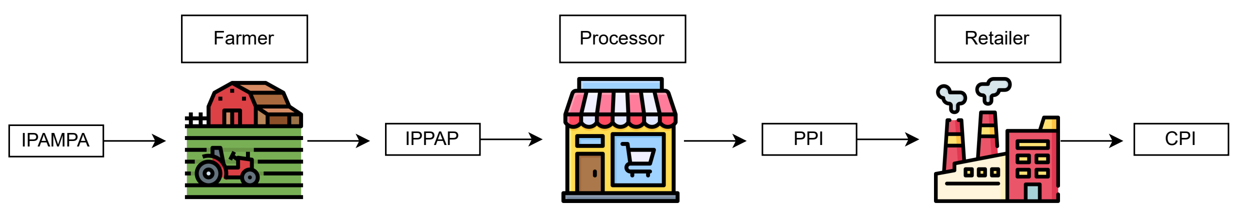
2 Data

In this section, I begin by outlining the legislation governing contracts within the French food supply chain, as well as the major shocks that have affected it between 2015 and 2023. I then present the estimation strategy employed in this study, followed by a description of the dataset utilized for the analysis.

2.1 The French food supply chain between 2015 and 2023

The food supply chain studied in this paper is represented in Figure 1. It can be decomposed into three main nodes: farmers, processors, and retailers. This study focuses on the transmission of agricultural cost shocks faced by French processors to their output prices. Consequently, the products considered are those sold either to other processors, exported, or sold to retailers. In order to measure such transmission, it is important to have in mind the particularity of the legislation surrounding this supply chain, especially for products sold by processors to retailers.

Figure 1: Food supply chain with price and cost indices



Notes: This figure is a stylized representation of the supply chain studied in this paper along with the price and cost indices associated at each stage of the supply chain. IPAMPA is the Monthly Agricultural Means of Production Purchasing Price Index, IPPAP the Monthly Agricultural Producer Price Index, PPI the Monthly Producer Price Index in Industrial Production Sold in France for food industry and CPI is the Monthly Food Consumer Price Index
Source: Own

Contracting in the supply chain. In France, contracts between food processors and retailers are regulated by the Commercial Code. Typically, both parties agree on a reference price, as well as a set of prices corresponding to the quantities that retailers may purchase in specific months, along with the conditions for renegotiation. In addition, the parties must jointly establish a discount calendar to be applied during the bargaining period. Concerning price diffusion, several important modifications of this code are worth mentioning for the period 2015 - 2023.

The first major reform was the introduction of mandatory renegotiation clauses under the Hamon Law of March 17, 2014 (Article L441-8 of the Commercial Code), which may have accelerated the transmission of cost shocks by facilitating price adjustments within the contractual period.
The second reform established a mandatory annual contracting framework in April 2019 through the

Egalim 1 law. Since then, processors and retailers negotiate once per year, between December and February, with newly agreed contracts taking effect on March 1. This annual bargaining requirement applies only to products sold under processors' own brands and does not extend to private-label products[3]. By constraining price renegotiation to a specific window, this reform may have slowed the transmission of cost shocks for processors' branded goods.
Finally, in October 2021, *Egalim 2* law was enacted, introducing new rules for transactions along the food supply chain. These changes affected bargaining dynamics both upstream (between farmers and processors) and downstream (between processors and retailers) and aimed to increase the speed of the propagation of shocks that initially affected farmers. On the upstream side, the law mandates the use of written contracts for the sale of agricultural products, similar to those already mandated between processors and retailers. This requirement took effect in January 2023, except for beef and dairy products, which began on January 1, 2022. These contracts must include automatic price revision clauses and renegotiation conditions indexed to changes in agricultural production costs. Additionally, for beef products, the law introduced mandatory price tunnels, setting lower and upper thresholds that triggered automatic price reviews when exceeded. On the downstream side, the new legislation imposed automatic price reviews similar to those mandated for upstream contracts and specified that negotiations could no longer include agricultural cost share of production. This provision became effective immediately after the enactment of the law and was applied to the 2022 bargaining period. Those changes might have affected both the speed and magnitude of cost-shock transmission.

Overall, the objective of this study is not to evaluate the impact of these legislative reforms. In particular, the heterogeneity of the laws in terms of their timing of implementation and their specific provisions across product categories makes it difficult to credibly quantify their effects using the available dataset. Nevertheless, these institutional features provide important context and should be kept in mind when interpreting the results.

The rise of inflation. The major event affecting this supply chain is the rise of inflation in the recent years. Between January 2021 and January 2023, consumer food prices rose by 16 %, according to INSEE. In their report for the French Senate, Gremillet and Loisier (2022) attributed food inflation to shocks affecting various stages of the supply chain. The post-Covid economic recovery led to a sharp increase in energy, transportation, and packaging costs. Additionally, extreme weather conditions severely impacted cereal and oilseed crops, driving up production costs for farmers. These factors contributed to the initial surge in inflation at the end of 2021. Senators noted that the beginning of the Ukraine war further amplified inflationary pressures. The first channel was the subsequent energy crisis that seriously affected all actors in the industry. Moreover, it has driven

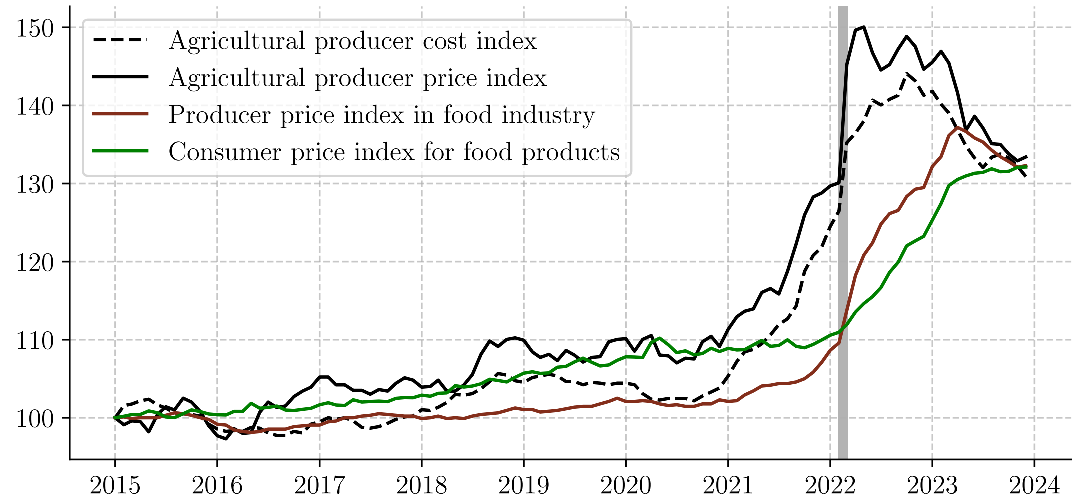
[3]Articles related to processors own products and retailers product are respectively L441-4 and L441-7.

up the costs of fertilizers and pesticides, further increasing expenses for farmers. The second was Ukraine's exports disruption, affecting global crop prices (as Ukraine was the sixth-largest exporter of corn and the seventh-largest exporter of wheat in 2021).[4]

This narrative can be illustrated using price indices that track developments at each stage of the food supply chain. A stylized representation of the French food supply chain is presented in Figure 1. For each node, the corresponding price indices capturing the evolution of input costs and output prices are reported. The associated time series are displayed in Figure 2. Inflationary pressures first became visible through an increase in both the '*Monthly Agricultural Means of Production Purchasing Price Index*' (IPAMPA, represented by the black dashed line) and the '*Monthly Agricultural Producer Price Index*' (IPPAP, shown by the solid black line) in 2021, followed by a second surge after the onset of the Ukraine war (marked by the gray vertical line). The figure highlights two core aspects of shock transmission within the supply chain: the pass-through, the elasticity of prices to cost shocks, and the timing of this pass-through. At this stage, the transmission seems to be instantaneous, with cost shocks being more than fully passed through to the prices. Examining further along the supply chain, we see an increase in both the '*Monthly Producer Price Index in Industrial Production Sold in France*' (PPI, represented by the red line) and the '*Monthly Food Consumer Price Index*' (CPI, represented by the green line). However, this surge appeared with a delay compared to the inflation at the farmer level, and its magnitude was lower. Table E2 in the Appendix presents the annual growth rates of all indices in Figure 2 across different periods. In 2021, most inflation occurred at the upstream stage, among farmers (with a 19.2 % increase in their costs and an 18.4 % rise in farm gate prices). In contrast, processing firms (hereafter, processors') experienced a lower but still significant inflation rate of 6.6 %, while consumers faced a relatively modest 1.7 % increase. In 2022, following the start of the Ukraine war, inflation surged at all stages of the supply chain. Upstream, inflation had a similar amplitude to that in 2021. Processors were the most affected, with a 23.5 % increase in factory gate prices, while consumers experienced a 14.7 % rise in the cost of food products.

[4] https://fas.usda.gov/sites/default/files/2022-04/Ukraine-Factsheet-April2022.pdf

Figure 2: Dynamic of inflation at all stages of the food supply chain in France between 2015 and 2024



Notes: This Figure contains the Monthly Agricultural Means of Production Purchasing Price Index (IPAMPA) in dashed black, Monthly Agricultural Producer Price Index (IPPAP) in black, Monthly Producer Price Index in Industrial Production Sold in France for food industry for domestic market in red and Monthly Food Consumer Price Index in green. All indices are based on 2015. The vertical gray line marks the start of the Ukraine war.
Source: INSEE
Coverage: France

The previous analysis at the macro level is likely to hide very heterogeneous situations in the food supply chain, which motivates the use of price data at the firm-level to specifically isolate the transmission of agricultural cost shocks to other simultaneous shocks.

2.2 Estimation strategy

The pass-through of agricultural cost shocks is the elasticity of processors' output prices with respect to a change in their unit cost triggered by changes in agricultural input prices. Specifically, let $\text{dlog UnitCost}_{ft}$ be the annual log change of unit cost for firm f and $\text{dlog OutputPrices}_{ft}$ be the annual log change of its output price index. We search for α defined as

$$\text{dlog OutputPrices}_{ft} = \alpha \, \text{dlog UnitCost}_{ft} + \epsilon_{ft}. \tag{1}$$

where ϵ_{ft} is a residual describing factors affecting the output price change that are not directly related to the change in unit cost (change in bargaining power, inflation anticipation, etc.).

I assume that we can separate the inputs of the firm into two categories. First, an agricultural input bundle whose price is AgPrice_{ft} and whose share in the total cost is S^{AG}_{ft}. Second, another bundle of inputs whose price is OtherPrice_{ft} which is composed of non-agricultural intermediate inputs, labor, electricity, and so on. Under the assumption that both are assembled through a Leontief production function and the unit input requirement for each of those bundles is constant (constant recipe for the agricultural bundle), we can write the change in unit cost as:

$$\text{dlog UnitCost}_{ft} = S^{AG}_{f} \, \text{dlog AgPrice}_{ft} + (1 - S^{AG}_{f}) \, \text{dlog OtherPrice}_{ft} \tag{2}$$

In my data, I have access to the output price at the product level. Products are classified into different categories according to the French Classification System (CPF). For each firm, I will construct an aggregate price index $\text{dlog OutputPrices}_{fct}$ at the fourth level of this classification, the *Class c*. I have access to the annual expenditure on agricultural inputs of the firm, from which I will derive the share of agricultural costs in the variable costs of the company. In addition to this share, I use agricultural expenditure to proxy the price of agricultural inputs. Under the assumption of a constant return to scale (1) and Leontief production function (2), I can estimate the agricultural price of products of Class c for firm f to agricultural expenditure through:

$$\text{dlog AgPrice}_{fct} = \text{dlog AgExpenditure}_{ft} - (\text{dlog TotalSales}_{ft} - \text{dlog OutputPrices}_{fct}). \tag{3}$$

with on the right-hand side of this equation, the annual change in agricultural expenditure, total sales, and output price. The estimation of α is performed using the following design:

$$\text{dlog OutputPrices}_{fct} = \alpha S^{AG}_{f} \times \text{dlog AgPrice}_{fct} + \text{dlog OutputPrices}_{fct-1} + \text{FE}_{ct} + \epsilon_{fct} \tag{4}$$

where, in this design, FE are Group $\times$ Year fixed effects with *Group* being the third level of the CPF. The coefficient α is identified from within-Group-Year variation in the agricultural cost shifter, which arises from two sources: cross-firm differences in the agricultural cost share S_f^{AG}, and cross-firm differences in the composition of agricultural inputs, reflected in dlog AgPrice_{fct}. The Group $\times$ Period fixed effects absorb any cost shock common to all firms within a product group in a given year, including shared non-agricultural input cost changes (energy, labor, packaging). The identifying assumption is therefore that, conditional on these fixed effects, the instrument is uncorrelated with firm-specific determinants of output price changes other than agricultural costs.

Using this design would yield a biased estimate of the pass-through as there might be some endogeneity issues related to the strategic adjustment of both the output and agricultural prices. Moreover, the approximation of agricultural prices comes with measurement issues. To deal with those issues, I instrument $S_f^{AG} \times \text{dlog AgPrice}_{fct}$ by a cost-shifter $S_f^{AG} \times \text{dlog AgPriceShifter}_{fct}$. The instrument exploits exogenous variation in farm-gate prices that shifts agricultural production costs and is assumed to influence the output price solely through this cost channel. It was constructed using product-level information. For each product g produced by processor f, I build an index that reflects the price of the agricultural inputs used in its production. I distinguish two cases in the construction of the instrument. For simple products (about 75 % of the sample), which rely on a single main agricultural input, this index is directly given by the corresponding input price index, and exposure is scaled by the firm-level agricultural cost share. For more complex products (about 25 % of the sample), I combine several agricultural input price indices using product-level input shares obtained from recipes of those products, sourced from OpenFoodFacts. Aggregating these product-level indices at the firm-level yields a shift-share instrument that captures the firm-level exposure to agricultural input price shocks. Multiplying this shift-share by the firm-level agricultural cost share provides a proxy for firm-specific agricultural cost shocks. A detailed description of this procedure is provided in the next subsection.

Concerns regarding the validity of the instrument. Because the cost shares of each input at the product level are not observed, I proxy them with the physical weight of each ingredient taken from product-level recipes. Using physical ingredient shares instead of true cost shares introduces a measurement error in the proxy for marginal cost variations, as low-value bulky inputs tend to be overweighted relative to high-value, low-weight inputs. Under standard assumptions, these limits generate attenuation bias, so that the estimated pass-through should be interpreted as a lower bound of the true elasticity of output prices with respect to agricultural marginal costs.

Since this instrument is constructed using input price indices, it is likely to be strongly correlated with agricultural expenditures. The validity of this instrument differs according to the type of product considered. For complex products, those that are linked to several input prices, the validity of the shift-share design relies on the exogeneity of either the shifts or the shares. For simple products, those that are linked to a unique input price, the validity of the instrument must rely on the exogeneity of the agricultural cost share and the shift. For some products, the shifts are based on international price indices (coffee, sugar, etc.), which domestic firms are unlikely to influence. However, for nationally determined price indices (cow milk, eggs, etc.), domestic processors may exert upstream market power and influence input prices, potentially weakening the exogeneity of the shift component (Avignon and Guigue, 2022).

Regarding the share, I will show that the agricultural cost share is quite stable over time, which implies that in a high-inflation environment, substitution between agricultural inputs and other inputs is limited. Moreover, I provide robustness in Appendix Table E10 to show that the time period on which the share is computed has a limited impact on the results. For complex products, I will assume that the production recipes are constant over time. Assuming time-invariant recipes abstracts from potential endogenous adjustments in the input composition in response to relative price changes. If firms substitute away from inputs whose prices increase, the effective marginal cost shock they face is dampened relative to the fixed-recipe counterfactual used to construct the instrument, which would further bias the estimated pass-through downward and weaken the first-stage relationship. A robustness test, where the pass-through is estimated only with simple products, is also provided to measure the impact of such a negative bias.

Finally, to analyze the timing of the propagation of shocks, I rely on both quarterly and monthly frequency data. At this frequency, firm-level agricultural expenditure data are not available. Therefore, I use a reduced-form specification in which I directly regress the changes in output prices on the instrument. In this setting, I do not interpret the level of the estimated coefficients but rather their statistical significance and dynamic profiles.

The next subsection presents the data used to build the different indices introduced in the regression design.

2.3 Data

In this subsection, I present the dataset used in the estimation of the pass-through. I will rely on firm-level agricultural input expenditure from the *Annual Sectoral Survey* (ESA), product level prices from *Observation of Prices in Industry and Services* (OPISE), firm-level balance sheet data (FARE). The period of interest is 2015 to 2023. For this study, the set of firms I will rely on is the one from the agri-food industry. The delimitation of this industry is taken from the one used in the *Annual Sectoral Survey*, from which I exclude wood processors (sectors 0220Z, 1610A, and 1610B in the A733 classification system) as well as tobacco and beverage processors (sectors 11 and 12 in the A88 classification system). Details of the remaining sectors are provided in Appendix Table E3.

Agricultural expenditures and cost-shares. I use a firm-level measure of agricultural expenditure sourced from the *Annual Sectoral Survey* (ESA). This survey, exhaustive for firms with more than 20 employees or 5 million euros of sales, mandates them to report the share of raw materials expenditure related to agricultural inputs, which corresponds to the purchase of raw agricultural inputs (e.g., milk) or a transformed version (e.g., butter)[5]. For each firm f and year t, I build the yearly log-change of agricultural expenditures dlog $\text{AgExpenditure}_{ft}$. Using firm-level annual balance-sheet data from FARE, I construct a measure of firm-level variable costs (the sum of wages, intermediate consumption and taxes) and build the annual share of agricultural expenditure in the variable costs of the firm S_{ft}^{AG} [6].

In the first column of Table 1, I report statistics on the distribution of total sales, total and log change of agricultural expenditure, and agricultural cost-share for firms that report positive sales in ESA. As ESA is exhaustive for large firms, the sample exhibits substantial right-skewness: median sales stand at approximately 3 million compared to a mean of 25 million, reflecting the coexistence of medium-sized establishments near the survey threshold and large industrial groups. A similar pattern characterizes agricultural expenditures, with a median of around 870 thousand euros against a mean close to 10 million euros. On average, agricultural inputs account for 35 percent of firms' variable costs, with a relatively low dispersion around the median (34 percent), indicating that reliance on agricultural raw materials is a defining feature of the food industry rather than a characteristic of a subset of firms. The annual log change in agricultural expenditure averages 4 percent over the sample period, with a standard deviation of 0.32, indicating considerable heterogeneity in expenditure dynamics across firms and years. Notably, the post-2020 subsample displays markedly higher growth rates—averaging 8 percent—consistent with the sharp rise in agricultural commodity prices observed during the 2021–2022 period.

Price data. As explained in the estimation strategy, the measurement of the pass-through relies on the processor output price indices and cost shifters.

Output price indices are constructed from product-level price data taken from "*Observation of*

[5] More precisely, the survey specifies that those are "materials, foodstuffs, or substances derived from agricultural production that are used in the production of intermediate goods and finished products. These products are either of plant origin (cereals, fruits, vegetables), mineral origin, or animal origin (milk, meat). They can be either raw (eggs) or processed (egg products). Finally, if synthetic raw materials are used, only those whose percentage of use is less than 50 % should be considered."

[6] As the firm may answer the survey before filing its balance-sheet information, it is possible to have higher agricultural expenditures than raw materials expenditures. I replace those agricultural expenditures with the level of raw material expenditures.

Table 1: Firm-Level Descriptive Statistics

	ESA			ESA × OPISE Final dataset			
Variable	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	t-stat
Sales	24951	2973	110971	251901	108692	360887	-9.85***
AgExpenditure	9838	867	47769	106867	40409	163092	-9.32***
dlog AgExpenditure	0.04	0.03	0.32	0.03	0.04	0.11	1.88*
post-2020	0.08	0.08	0.30	0.07	0.08	0.15	0.42
Agricultural cost-share	0.35	0.34	0.20	0.44	0.46	0.20	-7.74***
pre-2021	0.36	0.35	0.21	0.45	0.46	0.20	-6.64***

Notes: This table presents firm-level descriptive statistics for the food industry. Each firm's variables are first averaged across years (between 2015 and 2023) and then descriptive statistics are computed. The ESA includes all firms with positive agricultural expenditures in the year of the survey. ESA × OPISE includes firms that are present in the final dataset. dlog AgExpenditure denotes the log change in agricultural expenditure. The post-2020 variant includes only observations from 2021 onwards and pre-2021 includes observations up to 2020 included. The t-statistic tests for differences in means between the two samples (Welch's t-test). *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.
Source: ESA + FARE + OPISE
Coverage: Food industry firms in ESA and in the final dataset.

Prices in Industry and Services" (OPISE) survey between 2015 and 2023.[7] This dataset includes prices of goods representative of French industrial production, collected to construct the French Producer Price Index (PPI). Goods are categorized according to the French Classification System (CPF). Throughout the paper, I will use the term *Class* to refer to the fourth level (CPF4) of this classification (e.g., 'Dairy and cheese products') and *Group* for the third level (CPF3) (e.g. 'Dairy Products'). In this study, I focus on both domestic and export prices. The final dataset contains 7 Groups and 16 Classes.

Every five years, an INSEE investigator updates the list of products of a specific Class. He first chooses the list of firms to survey using a 40 % cut-off method on the annual sales: he selects the biggest firms operating in each Class in order to cover at least 40 % of the Class's total sales. Jointly with the financial directors of these firms, he constructs a list of goods representative of their production. Each month, firms are required to report the prices of their representative goods. This provides me with access to a price $\text{OutputPrices}_{gft}$ that a processor f charges for good g he sells during month t. The reported price is typically an average across different customers of the same type (eg., different retailers or different processors), which may mask instances of price discrimination. Using the name of the product, I identify intra-group sales and remove them from my dataset. I will later use the product name again to categorize the customers to which products are sold, as detailed in Appendix C.

[7] I stop in 2023. Covering 2024 would imply to label additional products since the composition of Classes are changing.

Construction of the agricultural price shifter. For each product in the dataset, I create an agricultural price shock that I will aggregate at the Firm $\times$ Class level to build my instrument. Let g be a good manufactured by firm f using a set of N_{gf} inputs. Then, the agricultural price shock specific to product g in Class c manufactured by firm f is:

$$\text{dlog AgPriceShifter}_{gfct} = \sum_{i}^{N_{gf}} \omega_i \text{dlog AgPriceShifter}_{it}$$

where ω_i denotes the cost share of input i in the production of good g, and dlog AgPriceShifter$_{it}$ represents the agricultural price shock affecting input i at time t. The cost shares ω_i are not directly observable in my data. However, I exploit information on product composition obtained from OpenFoodFacts, which provides detailed recipes for each product. I assume that, for a given product, the distribution of the physical weight of its ingredients is a reasonable proxy for the corresponding cost share. Ideally, one would rely on time-varying recipes to capture potential changes in the input composition; however, because OpenFoodFacts does not provide such temporal information, I assume that recipes remain constant over time. Using past shares in a high-inflation environment reinforces the exogenous characteristic of this price shifter.

Overall, I have two types of products: simple and complex products. Simple products are those with only one agricultural input each. I find it using the name of the good. For example, cow milk based dairy products are linked to cow milk, pasta to hard wheat, etc.[8] For more complex products, such as prepared meals, I manually extract the bar code and use the OpenFoodFacts API to obtain their recipes. In both cases, agricultural prices are sourced from IPPAP and complemented by quotations from *Réseau des Nouvelles des Marchés* (RNM), particularly for fish, for which there is no IPPAP covering the full period of interest.[9] Among the RNM prices, I select those collected at Rungis, which is one of the largest wholesale markets in France. For coffee I obtain worldwide prices from the Federal Reserve Bank of St. Louis and adjust them for exchange rate fluctuations. Information on product linkages and sources of the price indices is provided in Appendix Tables E4 and E6. The dataset is composed of approximately 75 % simple products, which mostly belong to the upstream classes. In contrast, complex products—those for which recipes are obtained from OpenFoodFacts—are assigned to more downstream classes in the supply chain, as they undergo a higher degree of transformation.

Merging datasets. Armed with these data, I construct three variables: the agricultural input cost shock at the Firm $\times$ Class $\times$ Period level, dlog AgPriceShifter$_{fct} \times S_f^{AG}$ (the instrument), and the annual change in agricultural expenditures scaled by the average agricultural cost

[8] Consequently for simple products, $N_{gf} = 1$ and $\omega_i = 1$.

[9] Note that, even if the period covers 2015–2023, to use lags, I need the inputs' price indices to cover at least 2013–2023.

share between 2012 and 2023[10], dlog AgPrice_{fct} (the regressor) and the change in the factory gate price index dlog $\text{OutputPrices}_{fct}$ (the variable of interest).[11] Both the instrument and variable of interest are built as an average of their product-level counterparts, dlog $\text{AgPriceShifter}_{gfct}$ and dlog $\text{OutputPrices}_{gfct}$. My estimation strategy relies on Group × Period fixed effects. Therefore, categories with more than eight observations were selected.

The final dataset is obtained by merging variables from ESA (changes in agricultural expenditure and cost shares) with the OPISE subsample for which I was able to construct an instrument. Table E3 compares the initial ESA dataset with the final dataset, which contains substantially fewer firms and accounts for approximately one-third of total sales. The dataset size shrank for three reasons. First, OPISE is a survey with a small cut-off (40 %) and therefore, covers only large firms. Second, input price indices are not available for all products, which reduces the size of the OPISE sample. Finally, it is not possible to obtain the recipe for each product because the product name might not be explicitly informative of the nature of the product or because the product is not in OpenFoodFacts. The resulting dataset contains 246 firms, with an average of ten firms per Class. I obtain 291 Firm × Class pairs that are surveyed for an average of 6.4 years[12]. For those times series, 89 of them are constructed using complex products.

In the second set of columns of Table 1 I report the statistics of the firms in the final dataset. As expected, given the OPISE sampling frame, the merged sample consists of significantly larger firms: the mean sales reach 252 million euros (compared to 25 million in the reference sample), and the mean agricultural expenditure exceeds 100 million euros. The t-statistics confirm that these differences are highly significant. Importantly, firms in the final sample also exhibit a higher agricultural cost share (44 versus 35 percent, $t = 7.74$), suggesting that OPISE disproportionately covers firms whose production is more intensive in agricultural inputs. Despite these level differences, the dynamics of agricultural expenditure remain comparable across samples: the log change in agricultural expenditure is not statistically different post-2020 ($t = 0.42$), and only marginally so over the full period ($t = 1.88$). This suggests that while my identification strategy relies on a selected sample of large, agriculture-intensive firms, the expenditure dynamics studied are broadly representative of the food industry.

Regarding output price representativeness, the final sample covers one-third of OPISE sales. Details on coverage are reported in Table E7; it is generally higher for upstream Classes, as their recipes are easier to obtain. Therefore, for those Classes, I will have a better external validity within the

[10] I choose a larger period than the one used for the regression in order to keep the larger number of observations. The average is taken on the set of years where the firm report its agricultural expenditures.

[11] The distribution of annual agricultural cost change ($S_f^{AG} \times$ dlog AgPrice_{ft}) is given in Appendix Figure F2 and the distribution of output price change (dlog $\text{OutputPrices}_{fct}$) is given in Appendix Figure F3. 37 % of the price changes are negative.

[12] Consequently, most firms are selling in one Class

Classes of the pass-through estimation. Moreover, as those Classes contribute significantly to the food PPI, I also have external validity of the pass-through for macroeconomic interpretation. To assess the quality of this coverage, I compare in Figure F4 the producer price index (PPI) computed from my dataset ("Sample") with two benchmarks: (i) the PPI calculated from the original dataset restricted to the selected Classes, and (ii) the PPI based on the full dataset. Between 2015 and 2022, the PPI from the final dataset exceeded the Food PPI from the full dataset, reflecting the specific composition of the sample. However, during the inflation period, all indices displayed similar growth rates. This convergence in trends is reassuring and supports the representativeness of the dataset.

2.4 Stylized facts

In this last subsection, I provide additional stylized facts regarding the distribution of agricultural cost shares and the time variation of variables of interest using data from the merged dataset.

Since my estimation strategy uses Group $\times$ Period fixed effects, I need heterogeneity of the agricultural cost-share within Group. As firms are primarily associated with products belonging to a single Class—a more disaggregated product category than Group—I examine the heterogeneity of the agricultural cost share both across and within Classes. In Figure F1, I report the distribution of the firm-level average agricultural share for firms with at least one product in my dataset. The average share is 44 %, with a lot of heterogeneity across Classes. Using an OLS with dummies for product categories, I find that 52 % of the variance is within 4-digit product categories (Classes) and 63 % within 3-digit (Groups), indicating the existence of different recipes or production functions for firms selling similar products. Therefore, I use this cross-sectional heterogeneity for my identification strategy. In Table 2, I present the average and standard deviation of this share per Class. I find that the average share seems to be correlated with the degree of upstreamness of the Class in the supply chain. For example, "Butcher's meat and slaughter products" has a much higher share than "Meat Products," for which outputs of the first Class sold to other processors are used as inputs of the second. It is the same with "Dairy products and cheeses" and "Ice creams and sorbets."

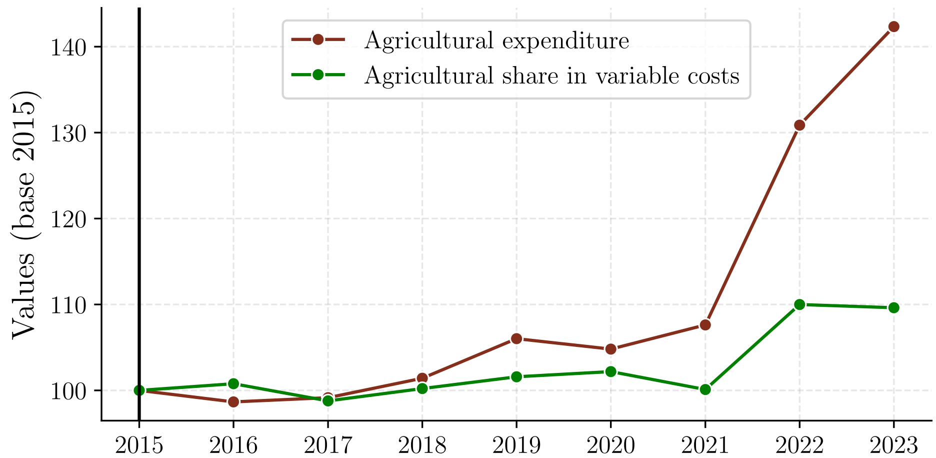
Table 2: Agricultural cost share per Class (in %).

	Mean	Std	# Firms
1011: Butcher's meat and slaughter products	64	15	43
1012: Poultry meat	51	11	23
1013: Meat products	51	11	47
1020: Processed fish	32	19	19
1031: Potato-based preparations and preserves	22	11	7
1032: Fruit and vegetable juices	32	12	11
1039: Processed fruits and vegetables	34	15	20
1051: Dairy products and cheeses	50	19	22
1052: Ice creams and sorbets	27	16	6
1061: Products of grain processing	49	17	21
1071: Bread, fresh pastries and pastries	36	16	10
1072: Rusks and biscuits, conservation pastries	30	9	6
1073: Pasta	33	7	10
1082: Cocoa, chocolate and confectionery products	27	19	8
1083: Processed coffee and tea	33	17	9
1085: Prepared meals	34	15	28

Notes: This table gives per Class (4-digit product category) statistics about the firm-level average of agricultural share in variable cost on the 2012 - 2023 period. The average, standard deviation, and number of firms per Class are given. The average agricultural cost-share is 44 % $\pm$ 19.
Source: ESA + FARE
Coverage: Processors of the food industry in the final dataset.

Another assumption I am using is the stability of the share over time. In my estimation strategy, such an assumption materializes through the use of the average share rather than its time-varying counterpart. To assess the quality of this hypothesis, I analyze the time variation of agricultural variables in the final dataset in Figure 3. I report the evolution of two indices: agricultural expenditure and agricultural cost-share. These indices are built using the same weights as those used to build the PPI to compare the evolution of factory gate prices to the input cost using a similar aggregation method. Both indices were set to 100 in 2015. Agricultural expenditures grew by 4.8 % between 2015 and 2020 and then rose by 34.7 %. During this high inflation period, agricultural cost-share rose by 9.5 % which is important but lower than expected if all cost would have remain stable. It could also be the case that processors used substitution strategies, which resulted in such stability. At the individual level, the high share of variation explained by firm fixed effects (88 %) indicates that agricultural shares are largely firm-specific and stable over time, with only 12 % of the variation stemming from within-firm fluctuations. Restricting the sample to 2015–2020 yields similar conclusions: within-firm variation remains limited (10 %), indicating that the aggregate rise in the agricultural share during the inflationary episode contributes little to individual-level variation. Overall, the increase of agricultural cost-share in the inflation period and the strong stability at the individual level support for the use of a firm-level average share in the regression.

Figure 3: Aggregate agricultural expenditures and agricultural cost-share indices and share between 2015–2023 (base year 2015).



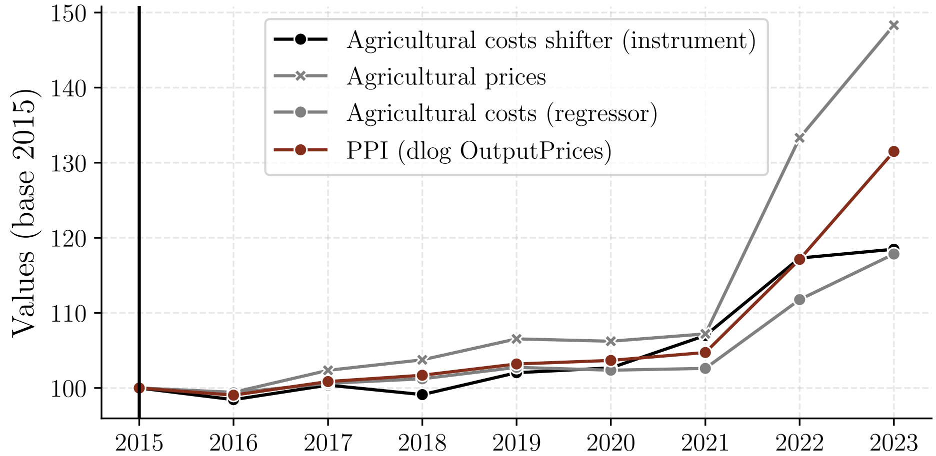
Notes: This figure shows indices constructed using the Laspeyres method for agricultural expenditures (AgExpenditure$_{ft}$) and the agricultural cost-share (S^{AG}_{ft}) between 2015 and 2023. The weights used in aggregation are the same as those employed to compute the PPI at the firm-level. The values were normalized to 100 in 2015.
Source: ESA + FARE
Coverage: Processors in the food industry included in the final dataset.

Finally, in Figure 4, I plot the indices describing the evolution of the three key variables: the instrument, regressor, and outcome variable. The rise of IPPAP observed in Figure 2 led to a an inflation of agricultural prices paid by French processors (red dashed line) of 41 % between 2021 and 2023.[13] Because agricultural expenditures account for an average of 44 % of processors' variable costs, this increase in agricultural prices implies a 15 % rise in agricultural unit costs. These higher input costs were subsequently transmitted to output prices and contributed substantially to the 26 % inflation observed in processors' selling prices[14]. The magnitude of this transmission is the goal of the next section.

[13]Here we are looking at change of yearly inflation rate, which is slightly different than the change of the level of IPPAP between January 2021 and January 2023.

[14]This inflation corresponds to the one in the final dataset and is slightly lower than the one observed in the food industry cf Figure F4.

Figure 4: Aggregate indices of the agricultural cost-shifter, input prices, and output prices (base year 2015).



Notes: This figure shows the evolution of the four series used in the empirical analysis: the agricultural input cost shifter ($S^{AG} \times d\log \text{AgPriceShifter}$ – black line), the annual change in agricultural prices ($d\log \text{AgPrice}$ – gray line with stars), the agricultural cost ($S^{AG}\, d\log \text{AgPrice}$ – gray line), and the change in processors' output prices ($d\log \text{OutputPrices}$ – red line). Indices are restricted to domestic sales and are constructed using the Laspeyres method with the same aggregation weights used to compute the PPI at the firm level. Values are normalized to 100 in 2015.

Source: ESA + FARE
Coverage: Processors in the food industry included in the final dataset.

3 Measuring the agricultural cost shock pass-through

3.1 Pass-through of agricultural cost shocks

In this section, I provide an estimation of the pass-through coefficient using the instrumental variable strategy described in Section 2.2.

Estimation. In Table 3, I present the reduced-form estimation of Equation 4 in Column (1), the OLS in Column (2), and the two-stage least squares (2SLS) estimates in Columns (3) and (4). The reduced-form specification is useful because it will be used at the quarterly frequency to estimate the dynamics of the propagation in Section 4. As expected, the estimate of this reduced form is lower than the 2SLS estimates. Indeed, as detailed in Appendix D, changes in farm-gate prices are the origin of the shock and occur upstream in the supply chain. Therefore, if an intermediary stands between the farmer and the processor, it may absorb part of the shock, which mechanically reduces covariance. The OLS specification yields an incomplete pass-through of approximately 38 %. As mentioned before, this estimate is likely to be downward biased due to endogeneity concerns and measurement errors. The 2SLS estimate addresses this concern by using an instrument that shifts the output price only through the change in agricultural price and is independent of the firm's decision. The high F-statistic of the first-stage results confirms that agricultural cost shocks are strong predictors of changes in agricultural spending. A 10 % increase in the agricultural cost shifter translates to a 3.9 % increase in firm-level agricultural costs. The corresponding second-stage estimates are substantially larger than the reduced-form coefficient, consistent with the expected direction of the bias from the measurement error. The 2SLS estimates indicate a pass-through of approximately 67%, which is statistically different from one, indicating that the pass-through of agricultural cost shocks is incomplete. It is possible to distinguish between products sold domestically and those exported. In Column (5), I restrict my sample to domestic products and find a 77 % pass-through, for which I cannot reject the full pass-through at the 1 % level. This higher pass-through is due to a lower pass-through for exported products, which I estimate in the next subsection. I have tried to test different heterogeneities, but the small sample I have with annual data does not provide consistent results. In particular, I do not find asymmetric pricing, state-dependent pass-through, or differences in pricing strategy for national or retailer brands (Peltzman, 2000; Hong and Li, 2017; Lafrogne-Joussier et al., 2023).

Table 3: Agricultural cost shock pass-through

	dlog $\text{OutputPrices}_{fct}$		dlog $\text{AgPrice}_{ft} \times S_f^{AG}$	dlog $\text{OutputPrices}_{fct}$	
	(1)	(2)	(3)	(4)	(5)
dlog $\text{AgPriceShifter}_{fct} \times S_f^{AG}$	0.259***		0.387***		
	(0.041)		(0.047)		
	[0.178, 0.340]		[0.295, 0.479]		
dlog $\text{AgPrice}_{ft} \times S_f^{AG}$		0.379***		0.670***	0.765***
		(0.022)		(0.093)	(0.110)
		[0.336, 0.423]		[0.488, 0.853]	[0.550, 0.980]
Group × Period FE	✓	✓	✓	✓	✓
Model	Reduced Form	OLS	First stage	2SLS	2SLS
F-test				68	51
Full pass-through (p-value)		0.0		0.0	0.032
Observations	2444	2444	2444	2444	1835

Notes: This table contains the estimation of agricultural cost shock pass-through using the reduced-form design in Column (1), the OLS in Column (2), the first stage in Column (3) and the second stage in Column (4). Column (5) contains the second stage for domestic products only. All specifications include Group × Period fixed effects. Estimation period: 2015 - 2023. Robust standard errors are given in parenthesis and 95% confidence intervals in brackets. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: OPISE + ESA + FARE
Coverage: Processors of the food industry in the final dataset.

Robustness. The previous estimation uses the change in agricultural expenditure adjusted for the change in input quantities consumed (cf. Equation 3). Concretely, this adjustment allows the growth rate of agricultural expenditure to proxy for the growth rate of agricultural input prices, rather than reflecting simultaneous changes in both prices and quantities. Table E8 examines how this quantity adjustment affects the pass-through estimates. Columns (1) and (2) report the first- and second-stage estimates without the adjustment, while Columns (3) and (4) present the results with the adjustment (corresponding to the main specification in the previous table). Adjusting for quantities appears to slightly reduce the negative bias in the first stage, which would otherwise inflate the pass-through estimate. Although the difference in the second stage is not statistically significant, I retain the adjusted measure as the main specification for robustness.

I provide additional robustnesses in Table E9. In Column (1), the baseline specification is reported. Since my observations are at the Firm × Class × Period level, it is possible that errors can be autocorrelated within the Firm dimension or the Class × Period one. Therefore, in Column (2), I estimate the pass-through using two-way clustering in both dimensions. This increases the size of the standard errors but still delivers incomplete pass-through. In Column (3), I use more granular fixed effects, replacing the Group × Period by the Class × Period. The pass-through increases up to 70% and remains incomplete. When INSEE's investigators create a list of products to survey with the manager of the firm, they also collect the total sales associated with each product to use them as weights. In Column (4), I use those to create the firm output and cost shifter indices. The estimated pass-through is very close to the main specification and is once again incomplete. In Column (5) I use weights of Column (5), aggregated at the firm-level to weight the OLS.[15] The resulting pass-

[15]Details regarding the use of sales information are given in Appendix B.

through is similar, and the standard error increases. For some products, I can differentiate if the price contains transportation costs (net) discounts (twice net) and other components of the contract with the retailer (3 × net). Using this differentiation, I construct price indices at the Firm × Class × Net level. The resulting dataset is composed of 25% of net, 65% of twice net and 10% of 3 × net indices. I obtain a similar incomplete pass-through when estimating using indices composed of only twice net prices (cf Column (6)).

Finally, robustness checks are provided regarding agricultural cost shares and complex products. In Figure 3, I show that, at the aggregate level, the agricultural cost share is quite stable between 2015 and 2020 and increases between 2021 and 2023. Moreover, I show that at the firm-level, there is little variation in the share over time. In Appendix Table E10, I test different specifications of the cost share. Using averages of the share over different periods or the contemporaneous share (S_{ft}^{AG}), the estimated pass-through remains fairly stable but is incomplete. However, when using the share from the previous year (S_{ft-1}), we can no longer reject full pass-through at the 10% significance level, and similarly at the 1% level when using the share from two years earlier. In these lagged specifications, however, the first-stage F-statistic is lower, and the sample size is slightly reduced. Another concern relates to the treatment of complex products. In Table E11, excluding these products from the sample yields a higher estimated pass-through, although the difference is not statistically significant. Moreover, despite the increase in magnitude, pass-through remains incomplete at the 5% level.

Incomplete pass-through. Finding incomplete pass-through in this context is not surprising, as similar results have been documented in various settings. Nakamura and Zerom (2010) find a one-fourth pass-through of coffee commodity price shocks into processors' prices. Since green bean coffee accounts for more than half of marginal costs, their 25% price-shock pass-through corresponds to a 50% cost-shock pass-through, an estimate in line with my agricultural pass-through.[16] Closer to my study, Avignon and Guigue (2022) document that a 10% increase in dairy product processors' marginal cost of production results in a 6.8% increase in output prices, a result in line with my estimate.

In a perfectly competitive environment, firms price at marginal cost and the pass-through of cost shocks is complete. Incomplete pass-through therefore points to imperfect competition in the environment in which processors operate. In the French food supply chain in 2020, there were 390 000 farms,[17] 17 000 legal units in the food industry, with 22 of them employing one third of the workers,[18]

[16]The cost-shock pass-through of an input equals the price-shock pass-through of that input, scaled by the input's share in marginal cost. In their structural estimation, going from a CES model with local costs to a discrete choice model reduces the price pass-through by 33%. This implies that firms pass through approximately 67% of marginal cost changes to prices, absorbing the remainder through markup adjustment.

[17]https://www.insee.fr/fr/statistiques/7728861?sommaire=7728903

[18]https://www.insee.fr/fr/statistiques/7728843?sommaire=7728903

and 360 retailers' brands.[19] Processors therefore have both upstream and downstream market power, each of which can generate incomplete pass-through through distinct channels.

On the upstream side, oligopsony implies that processors can substitute across suppliers or move along the supply curve to reduce their exposure to agricultural cost shocks (Amiti et al., 2014; Avignon and Guigue, 2022). These mechanisms can explain part of the incomplete pass-through of agricultural cost shocks into processors' changes in variable costs observed in Column (1) of Table 3, along with the heterogeneity of contracts mentioned above.

On the downstream side, oligopoly enables processors to set prices above marginal cost. When facing a cost increase, a processor that fully passes it through preserves its unit margin but loses demand. When the demand elasticity faced by the firm increases with price — that is, when the super-elasticity of demand is positive (Weyl and Fabinger, 2013; Klenow and Willis, 2016) — the firm finds it optimal to absorb part of the cost shock by compressing its markup rather than losing the increasingly price-sensitive marginal customers. This is the markup adjustment channel. In an oligopolistic setting, the relevant object is the firm-specific *perceived* elasticity, which incorporates both own-price effects and substitution toward competitors' products; the pass-through then depends on how this perceived elasticity varies with price, embedding strategic interactions within the same super-elasticity framework. A formal derivation of this mechanism, from the single-product monopolist case to the multi-product oligopoly, is provided in Appendix A.[20]

A key feature of my empirical design is that it allows for a clear identification of this downstream channel. Since the regressor is the change in the firm's actual agricultural expenditure — which already reflects any upstream adjustments due to monopsony power, substitution strategies, or contractual arrangements — the estimated pass-through coefficient $\hat{\alpha}$ captures the response of output prices to a change in the firm's realized marginal cost.[21] In other words, $\hat{\alpha} < 1$ can be attributed to downstream markup adjustment rather than to upstream cost absorption. Using a quantitative model that integrates both upstream and downstream market structures, Alviarez et al. (2023) find that ignoring two-sided market power could exaggerate tariff pass-through by approximately 60%, which underscores the importance of this distinction. This downstream pass-through is susceptible to variation across customers, a possibility that will be tested in the next subsection.

[19] https://www.insee.fr/fr/statistiques/7652356

[20] In the food market, demand functions encompass both the direct response to a price increase and the indirect responses through substitution effects. Those substitution effects play an important role for the bargaining between processors and retailers (Bonnet et al., 2021) and may therefore affect the level of the pass-through.

[21] This interpretation is cleanest for products whose agricultural input prices are determined on international markets (coffee, sugar), where domestic processors are unlikely to influence farm-gate prices. For products with nationally determined input prices (cow milk, eggs), processors may exert upstream market power that also affects the instrument, which could weaken both the exclusion restriction and the clean separation between upstream and downstream channels.

Finally, from a measurement perspective, it is possible that incomplete pass-through in logs masks complete pass-through in levels. Sangani (2023) document such a pattern in the retail sector. This occurs when firms set prices by adding a constant absolute margin to marginal cost rather than applying a constant proportional markup. Unfortunately, although I observe product prices in levels, I do not observe the corresponding input price shocks in levels or the necessary technical coefficients,[22] which prevents me from directly testing this hypothesis.

3.2 Customers

Using the name of the product, I can extract the information of the customer to whom the product is sold. The process is detailed in Appendix C along with the decomposition of the resulting dataset across customers. Overall, I have four categories of customers: processors, retailers, exports, and other customers. I split my Firm × Class × Period input and output indices to a Firm × Class × Customer × Period level. For each Class, I report the decomposition of the number of observations per customer in Table C1. Additionally, I use the total sales of each product to decompose the total sales of the Class across different customers. Products sold to retailers constitute the main type of customers and cover most of Classes. Products sold to processors contain a basket of products that is less diversified compared to the other categories, making the comparison of the estimated pass-through more complicated.

Table 4 presents the first (Panel A) and second stage (Panel B) estimation of the pass-through. I find that the transmission of agricultural cost shocks into agricultural expenditure is complete for products sold to processors but not for products sold to retailers. This pattern can be rationalized using product categories. Products sold to other processors are mostly raw products compared to those sold to other retailers. The length of the supply chain is supposed to decrease the first-stage coefficient, as explained above, which therefore leads to a higher first stage for products sold to other processors than for products sold to retailers. When restricting the first stage to Classes that contain products sold to processors, the first stage for retailers grows to $0.518 \in [0.33, 0.71]$: the difference with the first stage for products sold to processors is strongly reduced. Turning to the other customer categories, I do not find any statistical difference in the first stage between customers. The second stage shows that the pass-through is similar for processors and retailers, while it is lower for exported products and higher for the 'Other' category. However, these differences were not significant, which may be due to the small statistical power. Finally, we cannot reject the full pass-through at the 5 % level for the Retailer and 10 % for 'Other' categories, while we can reject it at the 1 % level for products sold to other processors or foreign customers.

[22] For example, the quantity of hard wheat required to produce one kilogram of pasta.

Table 4: Decomposition of the pass-through across customers

	Processor (1)	Retailer (2)	Export (3)	Other (4)
	Panel A. First stage			
dlog $\text{AgPriceShifter}_{fct} \times S_f^{AG}$	0.923***	0.277***	0.411***	0.559***
	(0.107)	(0.057)	(0.103)	(0.080)
	$[0.713, 1.133]$	$[0.165, 0.388]$	$[0.209, 0.612]$	$[0.402, 0.716]$
	Panel B. Second stage (IV)			
dlog $\text{AgPrice}_{ft} \times S_f^{AG}$	0.709***	0.717***	0.378*	0.908***
	(0.089)	(0.162)	(0.222)	(0.125)
	$[0.535, 0.884]$	$[0.399, 1.035]$	$[-0.059, 0.814]$	$[0.664, 1.153]$
Group × Period FE				
Model	2SLS	2SLS	2SLS	2SLS
F test	74	23	16	48
Full pass-through (p-value)	0.001	0.081	0.005	0.461
Observations	533	1499	609	608

Notes: This table contains the main pass-through regressions split by customer types. In Panel A, I report the first stage while in Panel B, I report the second stage. Robust standard errors are in parenthesis and 95% confidence interval is in brackets. All specifications contains Group × Period fixed effect and the past change of the firm price index as control. Estimation period: 2015 - 2023. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: OPISE + ESA + FARE
Coverage: Processors of the food industry in the final dataset.

3.3 Aggregate effect

During the recent period, what is the share of inflation at the producer level that can be accounted for by the transmission of agricultural cost shocks into factory gate prices? To answer this question, I use the prediction of my model for products sold in the domestic market. Therefore, I rely on the pass-through estimate of 76.5 %.

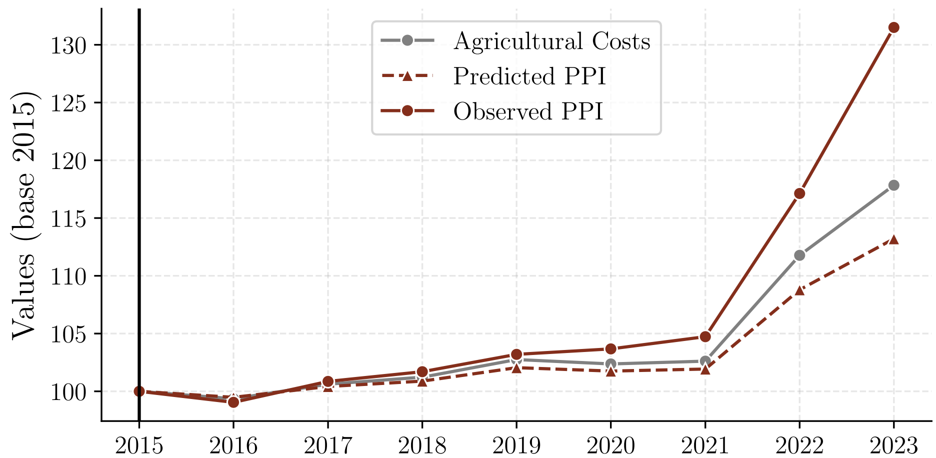
I follow Lafrogne-Joussier et al. (2023) and compute, for each firm in my dataset, the predicted price increase: $\text{dlog }\widehat{\text{OutputPrice}}_{fct} = \widehat{\alpha}\,\text{dlog AgPrice}_{ft} \times S_f^{AG}$. In Figure 5, the aggregate evolution of agricultural costs, predicted PPI, and observed PPI are reported. As mentioned before, between 2021 and 2023, agricultural prices paid by French processors rose by 41 %, which corresponds to an increase in agricultural costs of 15 %. Using a pass-through estimate of 76.5 %, I predict that this increase in agricultural costs would raise factory-gate prices by 11 %, which accounts for 42 % of the 26 % observed inflation in the estimation sample.[23]

The fact that agricultural cost inflation does not explain 100 % of the observed inflation can have several sources. First, agricultural costs account for less than half of the variable costs of firms in the dataset. Second, I measure the incomplete pass-through. Residual inflation can be attributed to increases in the prices of other inputs, such as energy (Aldama et al., 2025; Lafrogne-Joussier

[23] With a 15% rise in agricultural costs, full pass-through would have explained 57 % of the observed inflation.

et al., 2023; Arquié and Thie, 2023), some of which exhibit complete or even excess pass-through. Moreover, this unexplained part of the inflation could also be related to other components of the pricing strategy of the firm that are not related to marginal cost that I materialized in Equation 1 by ϵ_{ft} (diminishing of discounts, fixed fees added to the price...).

Figure 5: Aggregate indices of the observed PPI in the French food industry and the predicted PPI (base year 2015).



Notes: This figure shows the evolution of the three variables, the agricultural cost (S^{AG}dlog AgPrice – gray line) and the change of the observed (red line) and predicted PPI (dashed red line) using a pass-through of 0.765. All indices are constructed using the Laspeyres method, with the same aggregation weights used to compute the PPI at the firm-level. The weights used in aggregation are the same as those employed to compute the PPI at the firm-level. Values are normalized to 100 in 2015.
Source: ESA + FARE
Coverage: Processors in the food industry included in the final dataset.

Finally, this exercise assumes that common cost shocks are transmitted with the same magnitude as idiosyncratic shocks. In an oligopolistic environment, however, we can expect differential pass-through across these two types of disturbances. When a firm experiences an idiosyncratic cost shock, its pass-through is governed by two channels: the curvature of the demand function, which determines how the firm's optimal markup responds to a change in marginal cost, and the reallocation of demand toward competitors whose prices remain unchanged (cf Appendix A). Because the firm adjusts its price in isolation, it loses market share to rivals, which attenuates the price response. By contrast, the pass-through of common cost shocks depends critically on the extent of nominal rigidity, as emphasized by Wang and Werning (2022). When prices are fully flexible, all firms adjust simultaneously, so no demand reallocation occurs. Pass-through is then governed solely by the curvature channel, and the common shock is transmitted more completely than an idiosyncratic one. Under price stickiness, however, the logic changes. Firms that are able to reoptimize anticipate that a fraction of competitors will keep prices fixed. Adjusting fully to the common cost increase would therefore raise a firm's relative price vis-à-vis constrained competitors, triggering demand reallocation. The same two channels that govern idiosyncratic pass-through are now at play, and optimizing firms attenuate their price response accordingly.

In a high-inflation environment, prices become more flexible as the cost of nominal rigidity rises. Consequently, the pass-through of common cost shocks is likely to exceed that of idiosyncratic shocks: with all competitors adjusting simultaneously, firms can raise prices without losing relative position, thereby preserving their markups. The estimate I use, however, is identified from idiosyncratic variation in agricultural costs—variation that is orthogonal to competitors' cost movements. Applying this idiosyncratic pass-through rate to the common component of the 2021–2023 agricultural price surge therefore yields a lower bound on predicted inflation: actual pass-through of the common shock was likely higher, as firms could maintain markups more easily when all faced the same cost pressure.

4 The propagation of the shock

In the previous section, I measure the pass-through of agricultural cost shocks over a one-year horizon. However, it is possible that these shocks can take more than a year to be transmitted to factory gate prices. The timing of shock transmission using micro-level data has been analyzed in the literature. Lafrogne-Joussier et al. (2023) find that energy cost shocks are transmitted mostly in the first quarter after their occurrence into factory gate prices for all firms in the industry. Concerning food, Nakamura and Zerom (2010) show that it takes at least six quarters for coffee commodity cost shocks to be transmitted to wholesalers' output prices, with most of the shock being transmitted in the first semester. In their paper, such sluggishness is attributed to menu costs which force firms to delay the transmission of cost-shocks.

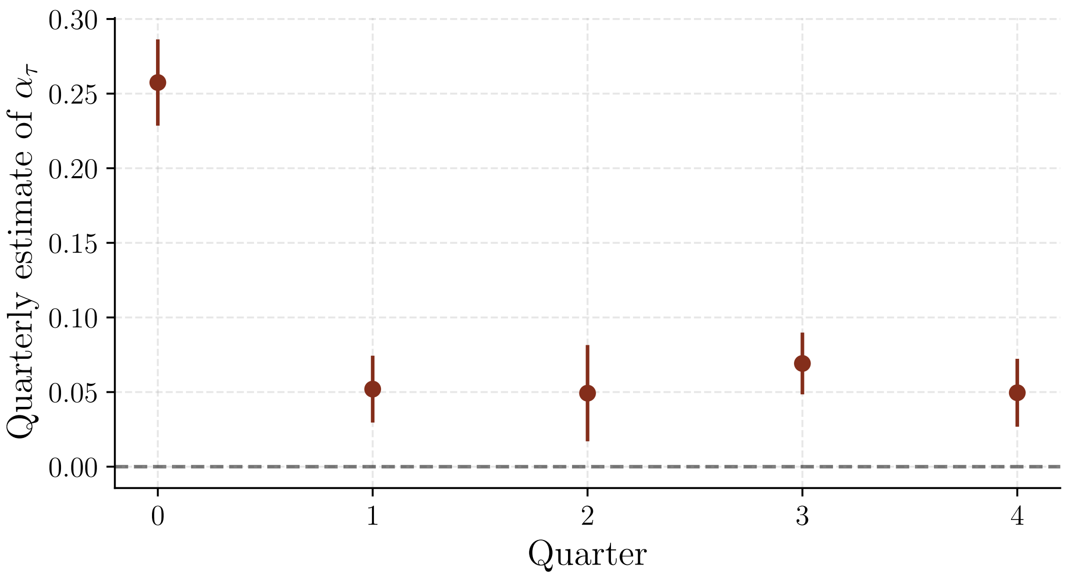
Ideally, to analyze the dynamics of the transmission, one would like to have a monthly or quarterly version of the 2SLS design. Agricultural farm gate prices (AgPriceShifter) and factory gate prices (OutputPrice) are available at the monthly frequency, but variable costs and agricultural expenditures are available at the annual frequency only. Therefore, the regressor (AgPrice) is only available at an annual frequency. Consequently, I will not rely on the 2SLS design but on the reduced-form version at the monthly and quarterly frequencies, where I will introduce lags in the right-hand side variable:

$$\text{dlog OutputPrice}_{gfct} = \sum_{\tau=0}^{\tau_{max}} \alpha_\tau \text{dlog AgPriceShifter}_{gfct-\tau} \times S_f^{AG} + \sum_{\tau=1}^{\tau_{max}} \nu_\tau \text{dlog OutputPrice}_{gfct-\tau} + \text{FE}_{ct} + \epsilon_{gfct} \quad (5)$$

Due to the absence of monthly data on manufacturers' agricultural expenditure, I am constrained to estimate the reduced form, although the advantage of this model is that I can use data at the product level (rather than Firm x Class). This significantly increases the size of my dataset, allowing me to use Class $\times$ Period fixed effects along with product fixed effects. As in the baseline estimation, identification comes from the heterogeneity of input shocks within a Class $\times$ Period and from variation in agricultural cost shares within a Class. It is important to keep in mind that α is not an estimate of the pass-through but rather the elasticity of the output price with respect to the instrument. In Appendix D I provide a detailed explanation of the difference between the elasticity measure in this regression and the notion of pass-through. Consequently, the magnitude of the estimate is not interpretable in terms of pass-through, but its significance is. Any positive and significant α_τ implies that an agricultural shock occurring at the farm-gate price takes τ quarters to be transmitted to factory-gate prices. To set τ_{max}, I follow Nakamura and Zerom (2010) and increase $\tau_{\max}$ until the first statistically insignificant coefficient is reached. The quarterly dataset contains 2226 products, 46, 461 observations, and the average lifetime of a product is 21 quarters (5.25 years).

The estimated coefficients are reported in Figure 6. The results indicate that an agricultural cost shock is transmitted within five quarters, with most of the adjustment occurring in the first quarter. Long-run transmission can be defined as the share of the initial shock transmitted over a given horizon, obtained by summing the estimated pass-through coefficients for that period. Based on this definition, I find that the first-quarter transmission accounts for 53% of the long-run transmission, the first semester for 68%, and the first year for 93%. Overall, the transmission of the shock is smaller than that observed in Nakamura and Zerom (2010) where more than 84% of the coffee commodity cost shock was transmitted in the first semester. Finally, finding that 93% of the shock is transmitted in the first year justifies not introducing lags in the 2SLS specification.

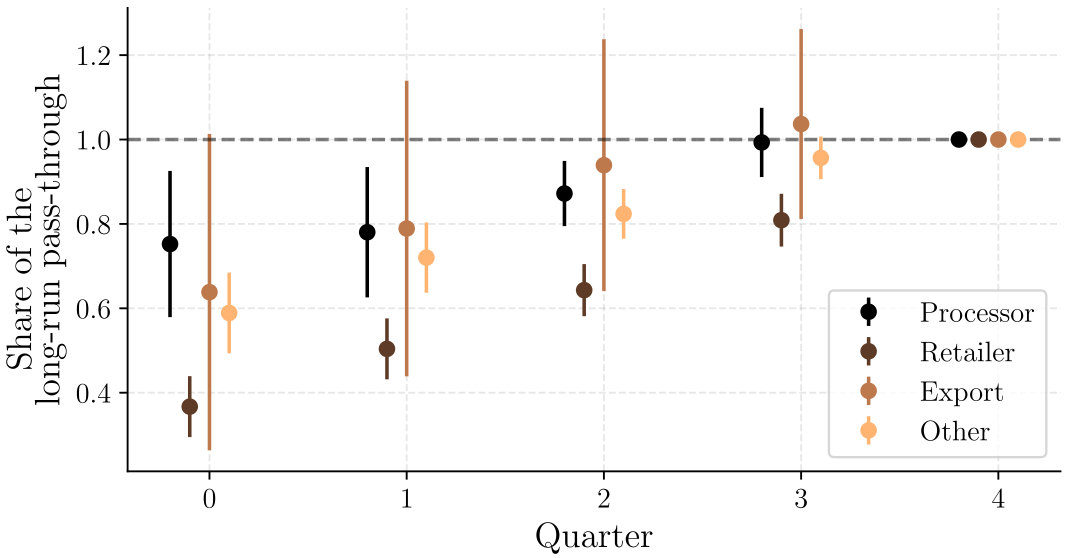
Figure 6: Propagation of farmer-gate cost-shocks at the quarterly frequency



Notes: Quarterly estimates of the elasticity of output prices to farmer-gate cost-shocks. All estimations include Product and Class $\times$ Period fixed effects. The confidence intervals were based on robust standard errors. Estimation period: 2015 - 2023. $\tau = 0$ is the contemporaneous quarter.
Source: OPISE + ESA + FARE
Coverage: Processors of the food industry in the final dataset.

Next, I exploit product-level customer information to examine whether the timing of cost-shock transmission differs across customer types. As discussed in Section 2, the regulatory framework governing products sold by processors to retailers may slow the transmission of shocks relative to products sold to other types of customers. To illustrate such difference I will estimate Equation 5 by interacting the cost shifter with customers. For ease of comparison across customers, Figure 7 reports the cumulative share of the long-run transmission after τ quarters for each group. The results reveal that the transmission is slower for products sold to retailers (approximately five quarters) than for those sold to other customers (approximately three quarters). This difference may reflect the longer supply chains for processors selling to retailers compared to those serving other customers. It could also reflect a difference in the timing of bargainings across customers. Bargaining with other processors can be done at any time, whereas bargaining with retailers is more constrained, as seen above. This also implies that the five-quarter adjustment observed in the aggregate results is largely driven by products sold to retailers.

Figure 7: Propagation of the shock at the quarterly frequency for different customers



Notes: This Figure displays the cumulative share of the shock that is being transmitted after each quarter and splitted across customers. All estimations include Product and Class $\times$ Period fixed effects. Confidence intervals are based on robust standard errors. Estimation period: 2015 - 2023. $\tau = 0$ is the contemporaneous quarter.
Source: OPISE + ESA + FARE
Coverage: Processors of the food industry in the final dataset.

Bargaining stages. The previous dynamic analysis abstracts from the fact that, since April 2019, prices for products sold by processors to retailers under their own brands can be adjusted only once per year, in March, following the annual bargaining stage. As a result, using quarterly changes in input and output prices outside the bargaining window may introduce measurement noise into the estimation. However, if renegotiation clauses are activated outside the annual bargaining period, exploiting quarterly variation may still enhance identification by capturing these adjustments. To assess this issue, I restrict the sample to the post–April 2019 period and to processors' own-brand products sold to retailers. Because private-label products are not subject to the annual contracting mechanism, they must be excluded from the analysis. I again rely on text analysis of product names to identify and remove such items. After April 2019, 38% of products sold to retailers are classified as retailer-brand products and are therefore excluded from the restricted sample.

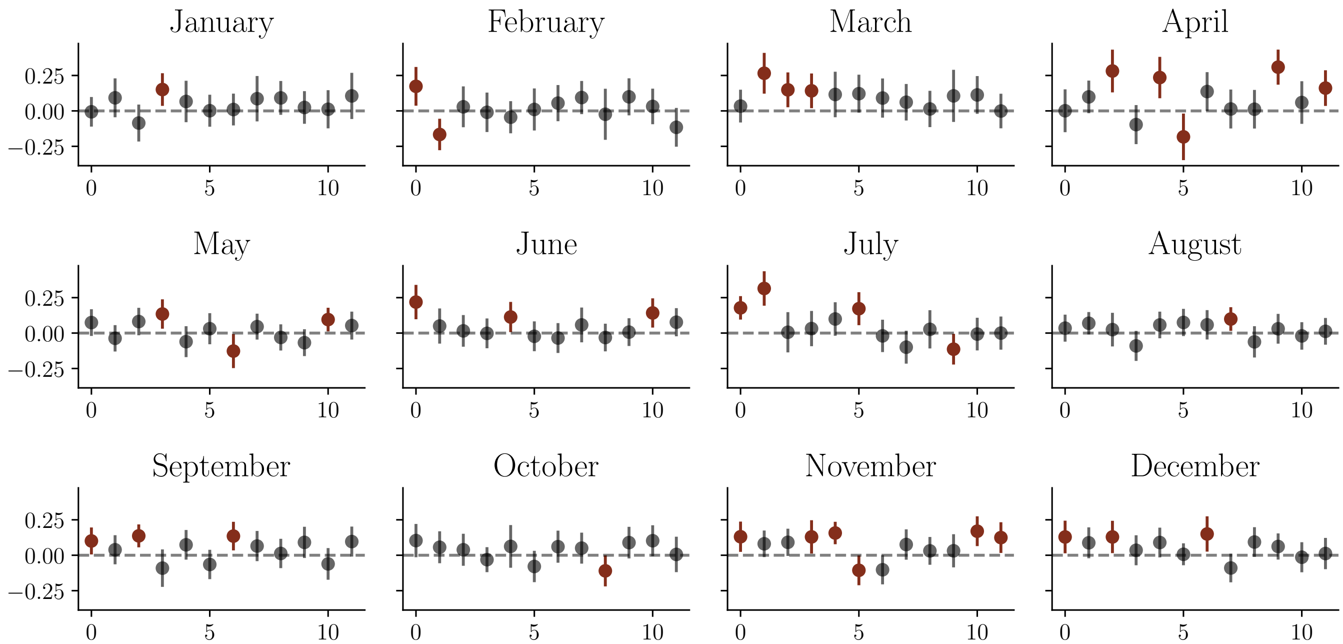
The resulting dataset, which is at the monthly frequency contains 18713 observations, and the average lifetime of a product is 33 months (2.8 years). I will estimate Equation 5 at the monthly frequency by interacting cost shocks with a dummy variable that specifies the month of the year. This leads to a monthly estimation of α_τ:

$$\begin{aligned} \text{dlog OutputPrices}_{gfct} = &\sum_{m=1}^{12}\sum_{\tau}^{12} \alpha_\tau^m \text{dlog AgPriceShifter}_{gfct-\tau} \times 1_{Month_t=m} \\ &+ \sum_{\tau=2}^{12} \nu_\tau \text{dlog OutputPrices}_{gfct-\tau} + FE + \epsilon_{gfct} \end{aligned} \tag{6}$$

The result of this estimation is reported in Figure 8 with significant coefficient in red to ease the reading. In each subplot, the horizontal axis represents the lag τ in months, where $\tau = 0$ corresponds to the contemporaneous month (e.g., for the March panel, $\tau = 0$ is March, $\tau = 1$ is February, and so on). The interpretation of a significant coefficient is as follows. Consider July, the change in factory-gate prices, dlog OutputPrice$_{gfct}$, is positively correlated with the agricultural cost shifter in July, as well as in June. This pattern indicates that the price change observed in July reflects the transmission of agricultural price shocks occurring in the preceding month. For, June, September, November, and December price changes are sensitive to the contemporaneous agricultural input cost-shock. Taken together, these results suggest that transmission is not confined to the formal bargaining window but also occurs outside it. In other words, cost shocks appear to be passed along the supply chain throughout the year, either through the activation of renegotiation clauses or via automatic price indexation mechanisms embedded in contracts.

March, however, appears to be a distinct month. Price changes in March are sensitive to shocks affecting a broader set of preceding months, but not to price changes in March itself. Intuitively, since annual negotiations take place between December and February, prices implemented in March likely reflect the outcome of these negotiations and therefore do not incorporate additional renegotiations occurring within March itself.

Figure 8: Effect of the bargaining calendar on shock's transmission



Notes: Monthly estimates of the pass-through coefficient for each month of the year. Statistically significant coefficient are marked in brown. Confidence intervals were constructed using robust standard errors. Estimation period: 2015 - 2023.
Source: OPISE + ESA + FARE
Coverage: Processors of the food industry in the final dataset.

The fact that transmission occurs outside the formal bargaining stages implies that farmers can pass shocks to processors, who in turn pass them on to their customers. One might be tempted to interpret this result in light of the *Egalim 2* law. However, cleanly identifying the causal impact of this reform requires a credible control group, which is not feasible without detailed information on the structure of the supply chain and the contractual arrangements linking farmers, processors, and retailers.

5 Conclusion

Between 2021 and 2023, rising agricultural and energy costs fueled food inflation in France, directly eroding household purchasing power. Therefore, understanding how such shocks propagate along the supply chain is central to designing effective policies. However, evidence has long been limited by the lack of detailed data linking agricultural inputs to industrial food prices in the country.

This study contributes to the literature by constructing a novel dataset that matches food products to their main agricultural inputs, covering a wide range of categories rather than focusing on a single commodity. Using this data, I show that processors transmit, on average, approximately 67% of agricultural cost shocks into their prices. Most of this adjustment occurs within a year, with evidence that shocks can also be passed outside annual bargaining stages.

The incomplete nature of this pass-through highlights the role of imperfect competition and bargaining power in a granular industry where farmers, processors, and retailers interact. More broadly, the findings quantify how shocks diffuse through the food supply chain, shedding light on the efficiency and timing of this transmission. By opening the black box of input-output linkages in food processing, this study provides a basis for further research and a tool for policymakers concerned with food-price stability.

Finally, the estimated pass-through provides only a partial view of the drivers of food inflation. By linking the dataset I constructed with retail-level data, it would be possible to trace how agricultural cost shocks are transmitted further downstream through retailers, thereby offering a more complete picture of the mechanisms behind food price dynamics.

References

Aldama, Pierre, Hervé Le Bihan, and Claire Le Gall, "What caused the post-pandemic inflation in France? An analysis using the Bernanke–Blanchard model," *Journal of Macroeconomics*, 2025, *85*, 103699.

Alviarez, Vanessa I., Michele Fioretti, Ken Kikkawa, and Monica Morlacco, "Two-Sided Market Power in Firm-to-Firm Trade," May 2023.

Amiti, Mary, Oleg Itskhoki, and Jozef Konings, "Importers, Exporters, and Exchange Rate Disconnect," *American Economic Review*, July 2014, *104* (7), 1942–1978.

_ , _ , and _ , "International Shocks, Variable Markups, and Domestic Prices," *The Review of Economic Studies*, November 2019, *86* (6), 2356–2402.

Arquié, Axelle and Malte Thie, "Energy, Inflation and Market Power: Excess Pass-Through in France," Working Papers 2023-16, CEPII 2023.

Avignon, Rémi and Etienne Guigue, "Markups and markdowns in the french dairy market," Technical Report, Technical report, mimeo 2022.

Bonnet, Céline, Zohra Bouamra-Mechemache, and Hugo Molina, "An Empirical Model of Bargaining with Equilibrium of Fear: Application to Retail Mergers in the French Soft Drink Industry," *SSRN Electronic Journal*, 2021.

Burstein, Ariel and Gita Gopinath, "International Prices and Exchange Rates," in "Handbook of International Economics," Vol. 4, Elsevier, 2014, pp. 391–451.

di Giovanni, Julian, Sebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A. Yildirim, "Global Supply Chain Pressures, International Trade, and Inflation," NBER Working Papers 30240, National Bureau of Economic Research, Inc July 2022.

Gremillet, Daniel and Anne-Catherine Loisier, "Négociations commerciales et inflation : des tensions inédites, des pratiques contestables," Technical Report 799, French Senat 2022.

Hong, Gee Hee and Nicholas Li, "Market Structure and Cost Pass-Through in Retail," *Review of Economics and Statistics*, March 2017, *99* (1), 151–166.

INSEE, "La conjoncture en France – mai 2023," Note de conjoncture, Institut national de la statistique et des études économiques May 2023.

Klenow, Peter J. and Jonathan L. Willis, "Real Rigidities and Nominal Price Changes," *Economica*, April 2016, *83* (331), 443–472.

Lafrogne-Joussier, Raphael, Julien Martin, and Isabelle Mejean, "Transmission des coûts et hausse de l'inflation," *Documents de travail No 2023-13*, 2023.

Nakamura, EMI and DAWIT Zerom, "Accounting for Incomplete Pass-Through," *The Review of Economic Studies*, 2010, *77* (3), 1192–1230.

Peltzman, Sam, "Prices Rise Faster than They Fall," *Journal of Political Economy*, 2000, *108* (3), 466–502.

Sangani, Kunal, "Pass-Through in Levels and the Unequal Incidence of Commodity Shocks," *SSRN Electronic Journal*, 2023.

Wang, Olivier and Iván Werning, "Dynamic Oligopoly and Price Stickiness," *American Economic Review*, August 2022, *112* (8), 2815–2849.

Weyl, E. Glen and Michal Fabinger, "Pass-Through as an Economic Tool: Principles of Incidence under Imperfect Competition," *Journal of Political Economy*, 2013, *121* (3), 528–583.

A Markup adjustment

In this subsection, I outline the theoretical foundation of the markup-adjustment channel. I present a highly stylized version of the mechanism for a price-making firm, while more general treatments can be found in Weyl and Fabinger (2013).

Consider a firm that sets its price P facing the demand function $Q(P)$. Its production cost is given by $C(Q)$, so that the firm chooses P to maximize profits as follows:

$$\max_P \; PQ(P) - C(Q(P)).$$

The optimal price-setting condition implies that the firm charges a markup μ over the marginal cost of production C_m, given by Lerner's formula:

$$\mu = \frac{P - C_m}{P} = \frac{1}{\epsilon_D},$$

where ϵ_D denotes the (absolute value of) price elasticity of demand. If ϵ_D is constant — for instance, if demand takes the form $Q = AP^{-\epsilon_D}$ with A being a constant — the markup is constant, and any change in marginal cost is fully passed through to the selling price P. In the more general case where ϵ_D depends on P, a shock to the marginal cost C_m changes the price according to

$$\frac{dP}{dC_m} = \frac{\epsilon_D}{\epsilon_D - 1} \cdot \frac{1}{1 + \frac{1}{\epsilon_D - 1} \cdot \frac{P}{\epsilon_D} \cdot \frac{d\epsilon_D}{dP}}.$$

Using Lerner's formula, $\frac{\epsilon_D}{\epsilon_D - 1} = \frac{P}{C_m}$, so:

$$\frac{C_m}{P} \cdot \frac{dP}{dC_m} = \frac{1}{1 + \frac{1}{\epsilon_D - 1} \cdot \frac{P}{\epsilon_D} \cdot \frac{d\epsilon_D}{dP}}.$$

Thus, the pass-through rate depends jointly on the level of demand elasticity and on its slope with respect to price—that is, on the curvature of the demand function. In the benchmark case of constant elasticity, pass-through is complete in logs. More generally, when elasticity varies with price, pass-through is incomplete because an increase in marginal cost leads the firm to adjust its price while endogenously compressing its markup to mitigate the induced decline in demand. This mechanism is governed by the term

$$\frac{P}{\epsilon_D} \cdot \frac{d\epsilon_D}{dP},$$

which corresponds to the super-elasticity of demand introduced by Klenow and Willis (2016). When this term is positive—so that demand becomes more elastic as price rises—optimal pricing implies pass-through below unity, as part of the cost shock is absorbed through a reduction

This derivation assumes a single-product monopolist, but the mechanism extends naturally to oligopolistic settings. Consider a Bertrand–Nash oligopoly in which each firm sets the price of its product taking as given the prices of its competitors. For expositional consistency, let $Q_k(P)$ denote the demand for product k as a function of the vector of prices P, and let $C_k(Q_k)$ denote its cost function with marginal cost $C_{m,k}$. Firm f, producing the set of products $\mathcal{F}$, chooses $\{P_k\}_{k\in\mathcal{F}}$ to maximize

$$\Pi_f = \sum_{k\in\mathcal{F}} \left[P_k Q_k(P) - C_k\big(Q_k(P)\big) \right].$$

The first-order condition for product $k \in \mathcal{F}$ is

$$Q_k(P) + \sum_{j \in \mathcal{F}} (P_j - C_{m,j}) \frac{\partial Q_j(P)}{\partial P_k} = 0.$$

This condition generalizes Lerner's formula: the markup on product k depends on a firm-specific perceived elasticity that incorporates both own- and cross-price effects within the firm's product portfolio. Accordingly, the pass-through of a change in marginal cost $C_{m,k}$ into price P_k is governed by how this perceived elasticity varies with prices—that is, by a generalized super-elasticity reflecting strategic interactions. When a firm raises its price, it loses demand not only because of the direct own-price effect but also through substitution toward competing products; the rate at which this competitive pressure intensifies as price increases determines the extent of markup compression. As shown formally by Weyl and Fabinger (2013), the pass-through formula in imperfectly competitive settings can be expressed by replacing the demand curvature term with a *conduct-adjusted* curvature that nests monopoly and perfect competition as special cases.

B Building weights at the firm-level

During the interviews between the INSEE investigator and the financial director of each firm, the investigator collects data on the total sales of each product for the previous year, which serves as the basis for the weighting of the PPI. Whenever there is a change in the composition of the class-level PPI, the weights are adjusted accordingly to reflect these changes. As a result, comparisons between these weights can only be made within a class and over the same period. I name s_{gfct} the total sales of product g in class c manufactured by firm f at time t. I first use it as a weight to create the Firm $\times$ Class level input and output prices for Column (4) of Table E9. In addition, I aggregate them to obtain the total sales at the same level: s_{fbt}. In Column (5) of the same table, I weight the regression using a corrected version of those weights that make them comparable across classes, such that the regression accounts for the missing part of OPISE I does not cover. Those are:

$$\tilde{s}_{fbt} = \frac{s_{fbt}}{\sum_{f,b} s_{fbt}} S_t$$

with S_t being the sum of the sales in each Class c taken from national accounting. Therefore, when summing the sales across Classes, I am able to recover the total sales of OPISE. Finally, I use s_{fbt} to assess within each Class the coverage of my dataset, for example, in Tables E7 and C1.

C Consumer's classification

Product names can contain information about the consumer for whom the product is being sold. I have chosen to classify the product into four categories: Processor, Retailer, Export and Other. The first processing step is to identify products that are sold within the group and remove them. The Processor category stands for products that are sold directly to the industry or processors. These products contain tags such as "industrial purpose" or the name of the consumer that I can manually classify as a processor. Moreover, the nature of the product is used for classification. For example, if the product is an entire calf, it will be assigned to the "Processor" because it cannot be sold directly to the consumer. The retailer is contained by product where the mention "*sold to X*" is being given where X can stand either for "retailer" or is the specific name of a French retailer. A product is also assigned to a retailer if it is a retailer's brand. The retailer category is not conservative in the sense that if a product is a transformed product with an explicit brand but for which I have no mention of it being sold to retailers, then we will categorize its customer as a retailer. Finally, products for which I can find a recipe can be found through OpenFoodFact are also assigned to the retailer category if they have not been classified into one of the categories mentioned above. The export category contains all products that are exported. The `INDICATEUR` variable in the dataset distinguishes whether the product is sold domestically or exported; I use it to classify products in the export category. Using the product name, I identified a small fraction of products sold to fast food, collective restaurants, or independent shops. The size of this category is very small; therefore, I merge those products with products that I am unable to categorize in the "Other" category.

The classification allows me to identify 268 products sold to other processors, 1074 to retailers, 332 are exported, and 401 are sold to 'Other' customers. In Section 3, I construct output prices at the Firm $\times$ Class $\times$ Customer $\times$ Period level. To have a clear understanding of the composition of the resulting dataset, I compute the total sales for each of those output prices by aggregating the product-level sales. Then, for each Class, I decompose the total sales across customers and report the average of this decomposition across years in Table C1. I also decompose the number of observations per Class I and report its average in the same table. Because the retailer category has many more products, it captures most of the sales in each class. The processor category is specific to a smaller sample of Classes making it less comparable to the other categories.

Table C1: Statistics on the number and total sales each customer represents in each class

	Share of observation (%)				Share of Branche's value (%)			
	Processor	Retailer	Export	Other	Processor	Retailer	Export	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1011 : Butcher's meat and slaughter products	35	24	17	24	30	27	14	28
1012 : Poultry meat	27	38	27	7	27	51	13	9
1013 : Meat products	12	52	12	24	4	79	3	14
1020 : Processed fish	0	95	5	0	0	99	1	0
1031 : Potato-based preparations and preserves	0	94	0	6	0	95	0	5
1032 : Fruit and vegetable juices	0	56	26	18	0	75	9	16
1039 : Processed fruits and vegetables	0	55	20	25	0	68	12	20
1051 : Dairy products and cheeses	15	49	36	0	6	82	12	0
1052 : Ice creams and sorbets	0	63	37	0	0	74	26	0
1061 : Products of grain processing	38	31	0	31	38	20	0	42
1071 : Bread, fresh pastries and pastries	0	56	17	27	0	76	8	17
1072 : Rusks and biscuits, conservation pastries	0	87	13	0	0	98	2	0
1073 : Pasta	0	65	20	15	0	88	6	6
1082 : Cocoa, chocolate and confectionery products	0	38	27	35	0	48	9	43
1083 : Processed coffee and tea	0	54	22	25	0	75	14	11
1085 : Prepared meals	0	83	8	9	0	92	3	5

Notes: This table decomposes, within each class, (i) the average share of observations at the firm-level (columns (1) to (4)) and (ii) the average share of total sales (columns (5) to (8)) accounted for by each customer type. The underlying dataset aggregates price time series at the Firm $\times$ Class $\times$ Customer level. For the share of observations, I first compute—within each year and each Class—the number of time series for each customer type, express it as a share of all time series in that Class, and then average these shares over time. The share of a Class's sales is computed using total sales at the Firm $\times$ Class $\times$ Customer level. For example, in the Poultry meat Class, on average 27% of observations correspond to goods sold to other processors, which represent 27% of that Class' total sales. Details regarding the use of sales information are provided in Appendix B.
Source: OPISE
Coverage: Processors of the food industry in the final dataset.

D Measurement errors in the reduced-form estimate

Regressing the output price on the instrument, a price index measured at the farmer-gate prices, ignores the fact that this agricultural input price index, based on general market prices, may not correspond to the price actually paid by the company to its supplier. First, I do not observe the exact quality, composition, or characteristics of the products purchased by the firm. Second, the company may have negotiated specific prices with its suppliers, for instance, as part of a long-term contract. Finally, the company may not purchase raw agricultural products but rather pre-processed products supplied by other manufacturers. The last factor is illustrated by examining the case of a pasta processor, labeled (2). In general, this producer does not buy hard wheat directly but rather a processed version of wheat semolina. Thus, there is an intermediary (1) between the producer and the farmer who sells hard wheat. Following a shock, Δc, to the price of hard wheat, the semolina processor adjusts his price according to $\Delta p_1 = \alpha S_1^{AG} \Delta c$. Considering that this pass-through is constant across firms, the pasta producer adjusts his price, leading to:

$$\Delta p_2 = \alpha^2 S_2^{AG} S_1^{AG} \Delta c$$

If we would regress the factory gate price Δp_2 on the input cost shock $S_2^{AG}\Delta c$ we would estimate $\alpha^2 S_2^{AG}$ and therefore underestimate the real pass-through α. The more intermediaries between the farmer and the processor for which we observe output prices, the more downward-biased our estimate of the pass-through will be.

E Additional tables

Table E2: Annual Inflation Rates by Index (in %)

Index	Jan 21 - Jan 22	Jan 22 - Jan 23	Jan 21 - Jan 23
IPAMPA	19.2	17.3	36.5
IPPAP	18.4	15.8	34.2
PPI	6.6	23.5	30.1
CPI	1.7	14.7	16.4

Notes: This table shows the annual inflation rates for various indices that describe the cost and prices of different stages of the food supply chain. The inflation rates are computed using the indices in Figure 2.
Source: INSEE
Coverage: Food supply chain in France.

Table E3: Sectors composing the agri-food industry

Code	**Sector Name**
1011Z	Processing and preservation of butcher's meat
1012Z	Processing and preservation of poultry meat
1013A	Industrial preparation of meat-based products
1020Z	Processing and preservation of fish, crustaceans and molluscs
1031Z	Processing and preservation of potatoes
1032Z	Preparation of fruit and vegetable juices
1039A	Other processing and preservation of vegetables
1039B	Processing and preservation of fruits
1041A	Manufacture of crude oils and fats
1041B	Manufacture of refined oils and fats
1042Z	Manufacture of margarine and similar edible fats
1051A	Manufacture of liquid milk and fresh dairy products
1051B	Manufacture of butter
1051C	Manufacture of cheese
1051D	Manufacture of other dairy products
1052Z	Manufacture of ice cream and sorbets
1061A	Flour milling
1061B	Other grain processing activities
1062Z	Manufacture of starch products
1071A	Industrial manufacture of bread and fresh pastries
1072Z	Manufacture of biscuits, rusks and preserved pastries
1073Z	Manufacture of pasta
1081Z	Manufacture of sugar
1082Z	Manufacture of cocoa, chocolate and confectionery
1083Z	Processing of tea and coffee
1084Z	Manufacture of condiments and seasonings
1085Z	Manufacture of prepared meals
1086Z	Manufacture of homogenized and dietetic foods
1089Z	Manufacture of other food products n.e.c.
1091Z	Manufacture of animal feed for farm animals
1092Z	Manufacture of pet food

Notes: This table contains the sectors in the A732 French sectoral classification system that compose the subset of the agri-food industry used in this paper. The full set of sectors composing the agri-food industry is taken from Annual Sectoral Survey.

Table E4: Inputs used in each product category

Class	Inputs	Simple products	Complex products
1011: Butcher's meat and slaughter products	Cattle, Sheep, Pigs, Calves	399	0
1012: Poultry meat	Roasting ducks, Turkeys, Guinea fowl, Label guinea fowl, Label chicken, Standard chicken, OFF	110	3
1013: Meat products	Roasting ducks, Turkeys, Pigs, Calves	301	0
1020: Processed fish	Cod, Shrimp, Pollock, Monkfish, Meagre, Mackerel, Hake, Sardine, Salmon, Tuna, Trout	134	0
1031: Potato-based preparations and preserves	Potato	14	0
1032: Fruit and vegetable juices	Pineapple, Beetroot, Carrot, Orange, Apple, Grape, OFF	38	2
1039: Processed fruits and vegetables	Garlic, Carrot, Cauliflower, Spinach, Strawberry, Bean, Corn, Apple, OFF	38	44
1051: Dairy products and cheeses	Sheep's milk, Goat's milk, Cow's milk, OFF	138	117
1052: Ice creams and sorbets	OFF	0	59
1061: Products of grain processing	Hard wheat, Rice	83	0
1071: Bread, fresh pastries and pastries	Soft wheat, OFF	28	26
1072: Rusks and biscuits, conservation pastries	OFF	0	39
1073: Pasta	Hard wheat, OFF	56	5
1082: Cocoa, chocolate and confectionery products	OFF	0	70
1083: Processed coffee and tea	Chicory, Coffee, OFF	58	1
1085: Prepared meals	OFF	0	105
Total		**1397**	**471**

Notes: This table gives for each product I have in my original dataset the set price indices used as input prices. OFF stands for products for which I used a recipe from OpenFoodFacts and which are considered complex products.
Source: OPISE + IPPAP + RNM + FRED
Coverage: Inputs of products made by processors of the food industry in the final dataset.

Table E5: General Statistics: Industry Representativeness

	ESA	ESA × OPISE (Final Dataset)
Number of Firms	7,737	246
Average Total Sales	155038	47228
Average Total AgExpenditure	62381	20441
% of ESA CA Covered	-	30.45%
% of ESA AgExpenditure Covered	-	32.84%

Notes: This table presents industry-level statistics averaged across years (between 2015 and 2023). The ESA includes all firms with positive agricultural expenditures in the year of the survey. ESA × OPISE includes firms that are present in the final dataset. The coverage percentages represent the mean of the year-by-year ratios. All monetary values are expressed in millions of euros.
Source: ESA + FARE
Coverage: All firms in ESA and firms in both ESA and OPISE.

Table E6: Source of input price indices

Source	Inputs
RNM	Apple, Bean, Beetroot, Carrot, Cauliflower, Cod, Corn, Garlic, Grape, Hake, Mackerel, Meagre, Monkfish, Orange, Pineapple, Pollock, Potato, Salmon, Sardine, Shrimp, Spinach, Strawberry, Trout, Tuna
FRED	Coffee
PPI (import)	Rice
IPPAP or IPAMPA	Calves, Cattle, Chicory, Corn, Cow's milk, Goat's milk, Guinea fowl, Hard wheat, Label chicken, Label guinea fowl, Pigs, Roasting ducks, Sheep, Sheep's milk, Soft wheat, Standard chicken, Strawberry, Turkeys

Notes: This table gives the source of all price indices. FRED correspond to the data of the Federal Reserve Bank of Saint Louis, IPPAP and PPI are from INSEE and RNM are from Réseau des nouvelles des marchés.
Source: OPISE + IPPAP + RNM + FRED
Coverage: Inputs of products made by processors of the food industry in the final dataset.

Table E7: Coverage and number of firms per Class in the final dataset

	Coverage	# Firms	Branche importance (%)
1011 : Butcher's meat and slaughter products	68	43	10
1012 : Poultry meat	43	23	4
1013 : Meat products	53	47	8
1020 : Processed fish	26	19	2
1031 : Potato-based preparations and preserves	74	7	0
1032 : Fruit and vegetable juices	37	11	0
1039 : Processed fruits and vegetables	33	20	4
1051 : Dairy products and cheeses	49	22	18
1052 : Ice creams and sorbets	40	6	0
1061 : Products of grain processing	55	21	2
1071 : Bread, fresh pastries and pastries	27	10	15
1072 : Rusks and biscuits, conservation pastries	13	6	1
1073 : Pasta	62	10	0
1082 : Cocoa, chocolate and confectionery products	33	8	3
1083 : Processed coffee and tea	71	9	1
1085 : Prepared meals	32	28	3

Notes: Per class in (1), the coverage of my dataset with respect to the total sales of the class, (2) number of firms in the dataset (3) share of the Class in the total value of OPISE. For example, in the Poultry meat class, my dataset covers 43% of the total value, contains 23 firms and this Class account for 4% of OPISE before my restrictions. Only classes represented in my dataset are displayed, which accounts for 71% of the total sales recorded in OPISE. Details regarding the use of sales information are given in Appendix B.
Source: OPISE
Coverage: Processors of the food industry in the final dataset.

Table E8: Adjusting agricultural expenditure by change in quantities

	Raw prices		Quantity adjusted prices	
	ΔAgPrice$_{ft} \times S_f^{AG}$ (1)	ΔOutputPrices$_{fct}$ (2)	ΔAgPrice$_{ft} \times S_f^{AG}$ (3)	ΔOutputPrices$_{fct}$ (4)
dlog AgPriceShifter$_{fct} \times S_f^{AG}$	0.364***		0.387***	
	(0.049)		(0.047)	
	$[0.267, 0.461]$		$[0.295, 0.479]$	
dlog AgPrice$_{ft} \times S_f^{AG}$		0.713***		0.670***
		(0.138)		(0.093)
		$[0.443, 0.983]$		$[0.488, 0.853]$
Group × Period FE	✓	✓	✓	✓
Model	First stage	2SLS	First stage	2SLS
Adjusted	No	No	Yes	Yes
F-test		54		68
Full pass-through (p-value)		0.037		0.0
Observations	2444	2444	2444	2444

Notes: This table contains the estimation of agricultural cost shock pass-through using the 2SLS design for the change in agricultural expenditure in Columns (1) and (2) and its quantity adjusted version in Columns (3) and (4) which constitutes the main specification of this paper. Columns (1) and (3) report the first stage estimate and Columns (2) and (4) the second stage. All specifications include Groupe × period fixed effects. Robust standard errors are given in parenthesis and 95% confidence intervals in brackets. Estimation period: 2015 - 2023. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: OPISE + ESA + FARE
Coverage: Processors of the food industry in the final dataset.

Table E9: General robustness

	dlog OutputPrices$_{fct}$					
	Baseline (1)	Clustered SE (2)	Branche × Period FE (3)	Weighted indices (4)	Weighted IV (5)	Twice net prices (6)
dlog AgPrice$_{ft} \times S_f^{AG}$	0.670***	0.670***	0.714***	0.671***	0.623***	0.704***
	(0.093)	(0.131)	(0.093)	(0.094)	(0.122)	(0.093)
	$[0.488, 0.853]$	$[0.411, 0.929]$	$[0.531, 0.897]$	$[0.487, 0.855]$	$[0.384, 0.862]$	$[0.521, 0.887]$
Group × Period FE	✓	✓		✓	✓	✓
Branche × Period FE			✓			
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Std Errors.	Robust	Firm + Group × Period	Robust	Robust	Robust	Robust
F test	68	40	75	65	44	69
Full pass-through (p-value)	0.0	0.011	0.002	0.0	0.002	0.002
Observations	2444	2444	2444	2444	2444	1287

Notes: This table gives additional robustness for the pass-through estimated using 2SLS. Column (1) is the main specification with robust standard errors, while Column (2) is estimated with standard errors clustered at the Firm + Group × Period level. In Column (3) I use Class × Period fixed effects. In Column (4) I report the main specification estimated using weighted versions of the firm level indices and in Column (5) I weight the regression of Column (4). In Column (6) indices are constructed only using twice net prices which are prices including discounts. Standard errors are given in parenthesis and 95% confidence intervals in brackets. Estimation period: 2015 - 2023. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: OPISE + ESA + FARE
Coverage: Processors of the food industry in the final dataset.

Table E10: Robustness for different agricultural cost-shares

	dlog OutputPrices$_{fct}$					
	Baseline	Average 2012 - 2015	Average 2012 - 2019	Current share	Lagged One year	Lagged Two years
	(1)	(2)	(3)	(4)	(5)	(6)
dlog AgPrice$_{ft}$ $\times$ S_f^{AG}	0.670***	0.562***	0.633***	0.681***	0.839***	0.761***
	(0.093)	(0.090)	(0.090)	(0.091)	(0.115)	(0.106)
	[0.488, 0.853]	[0.386, 0.738]	[0.457, 0.808]	[0.504, 0.859]	[0.613, 1.064]	[0.554, 0.969]
Group $\times$ Period FE						
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
F test	68	89	80	67	51	61
Full pass-through (p-value)	0.0	0.0	0.0	0.0	0.161	0.024
Observations	2444	2116	2414	2399	2392	2264

Notes: This table gives additional robustness for the pass-through estimated using 2SLS using different cost-shares. Column (1) is the main specification where the share is the average share between 2012 - 2023. Column (2) use the average share on 2012 - 2015, Column (3) the average on 2012 - 2019. Column (4) uses the contemporaneous share (S_{ft}^{AG}), Column (5) the lagged share (S_{ft-1}^{AG}) and column (6) the two years lagged share (S_{ft-2}^{AG}). All specifications have robust standard errors which are given in parenthesis. 95% confidence intervals in brackets. Estimation period: 2015 - 2023. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: OPISE + ESA + FARE

Coverage: Processors of the food industry in the final dataset.

Table E11: Removing product from OpenFoodFacts

	dlog OutputPrices$_{fct}$		dlog AgPrice$_{ft}$ $\times$ S_f^{AG}	dlog OutputPrices$_{fct}$	
	(1)	(2)	(3)	(4)	(5)
dlog AgPriceShifter$_{fct}$ $\times$ S_f^{AG}	0.340***		0.496***		
	(0.050)		(0.054)		
	[0.242, 0.438]		[0.390, 0.601]		
dlog AgPrice$_{ft}$ $\times$ S_f^{AG}		0.368***		0.686***	0.782***
		(0.024)		(0.087)	(0.100)
		[0.320, 0.415]		[0.515, 0.856]	[0.586, 0.978]
Group $\times$ Period FE	✓	✓	✓	✓	✓
Model	Reduced Form	OLS	First stage	2SLS	2SLS
F-test				84	64
Full pass-through (p-value)		0.0		0.0	0.029
Observations	1895	1895	1895	1895	1445

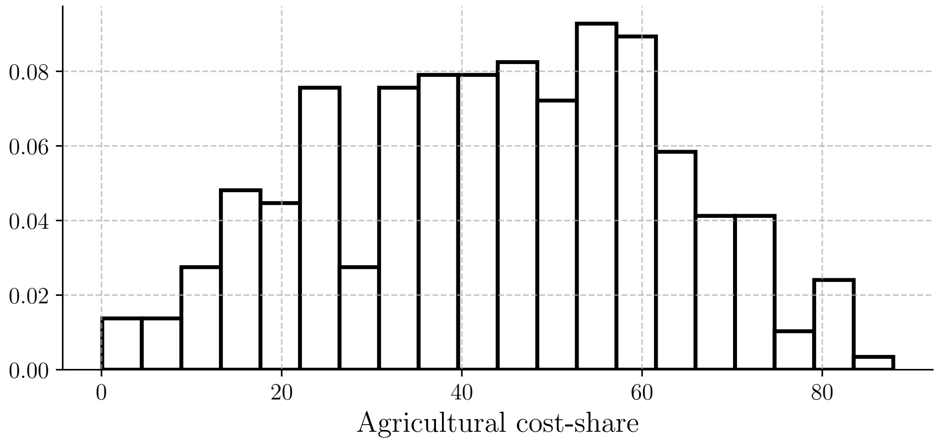
Notes: This table contains the estimation of agricultural cost shock pass-through without products from OpenFoodFacts. The reduced-form design is in Column (1), the OLS in Column (2), the first stage in Column (3) and the second stage in Column (4). Column (5) contains the second stage for domestic products only. All specifications include Group $\times$ Period fixed effects. Estimation period: 2015 - 2023. Robust standard errors are given in parenthesis and 95% confidence intervals in brackets. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: OPISE + ESA + FARE

Coverage: Processors of the food industry in the final dataset.

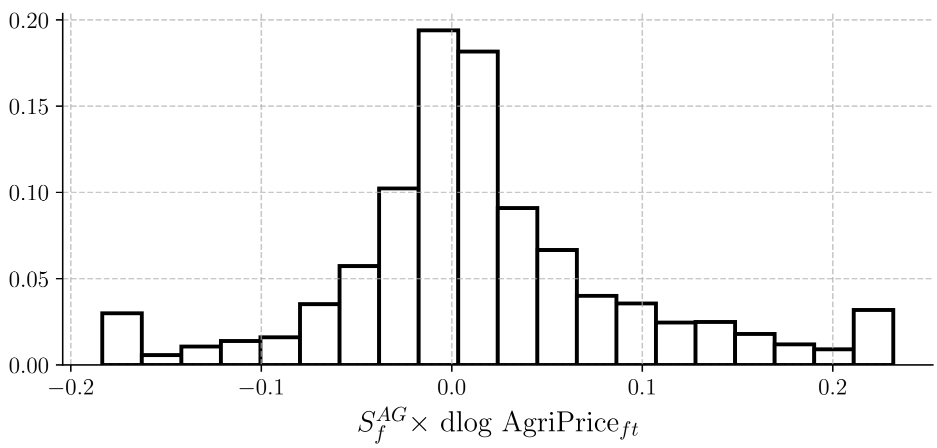
F Additional figures

Figure F1: Distribution of agricultural share



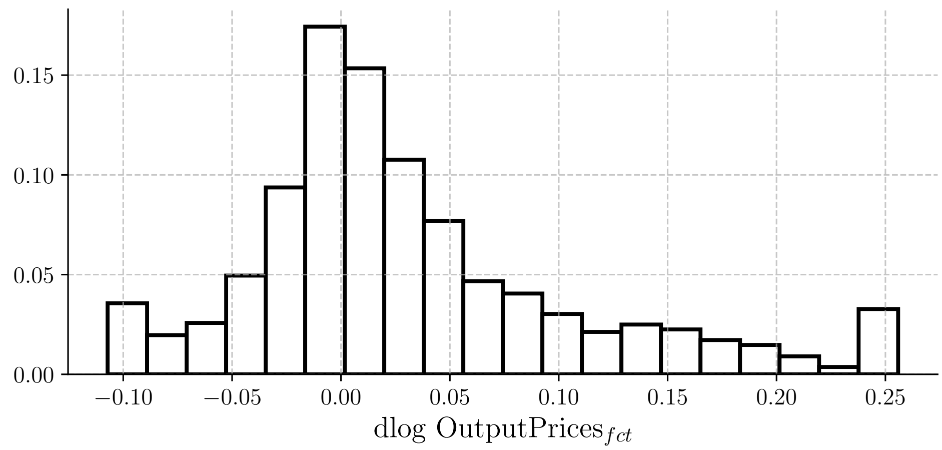
Note: Distribution of the agricultural cost-share averaged on 2012-2023 at the firm-level. The y-axis represents the number of firms. The average value of this distribution is $44\% \pm 19$.
Source: ESA + FARE
Coverage: Processors of the food industry in the final dataset.

Figure F2: Distribution of Firm-level change in agricultural cost



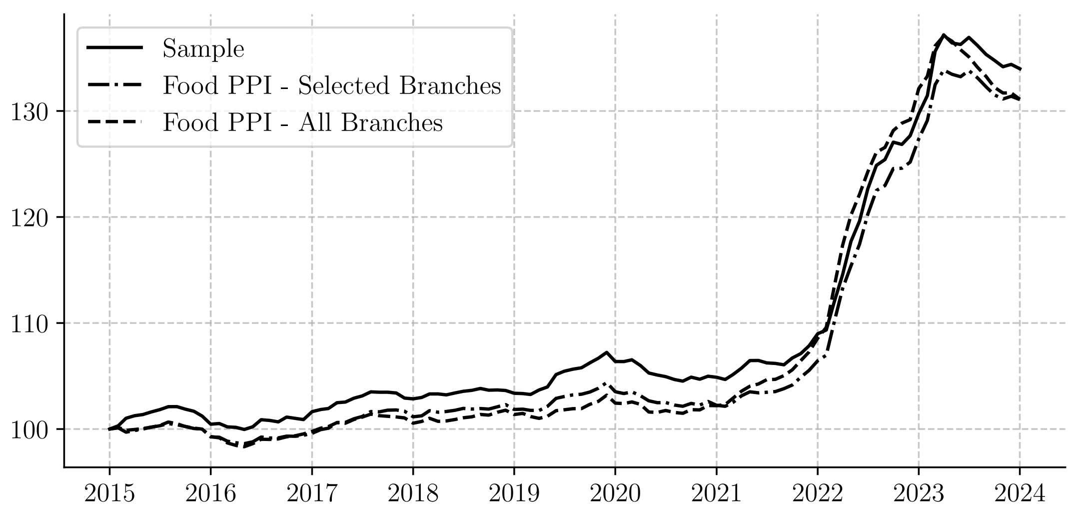
Note: Distribution of Firm-level change in agricultural cost. Mean $1.5\% \pm 7.5$. Period: 2015-2023. The y-axis represents the number of observations.
Source: OPISE
Coverage: Processors of the food industry in the final dataset.

Figure F3: Distribution of Firm × Class-level output price change



Note: Distribution of Firm × Class-level output price change. Period: 2015-2023. Mean 2.8% ± 7. The y-axis represents the number of observations. **Source**: OPISE
Coverage: Processors of the food industry in the final dataset.

Figure F4: PPI Constructed Using the Final Dataset vs. Food PPI



Notes: This figure displays price indices constructed using Laspeyres's method for three datasets: the final dataset (”Sample”), the original dataset restricted to selected Classes (”Food PPI – Selected Classes”), and the full original dataset including all Classes (”Food PPI – All Classes”).
Source: Domestic and export prices from OPISE
Coverage: Processors of the food industry in the final dataset.